# Extreme Value Analysis of Hong Kong's Stock Market

KAM Ying Chuen

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**Abstract of thesis entitled:**

**Extreme Value Analysis of Hong Kong's Stock Market**

**Submitted by Kam Ying-chuen**

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I study the extreme values or tail behavior of both minute-by-minute (from April 1, 1989 to March 31, 1999) and daily (December 8, 1972 to March) Hang Seng Index returns. Following Tsay (1999), I focus on observations that exceed certain thresholds and on their excesses over these thresholds. The exceedance times and the excesses are assumed to follow a two-dimensional Poisson process. The major findings are: i) the volatility of the Hong Kong stock market is higher after the Asian Financial Crisis period; ii) both minute-by-minute and daily stock returns do not follow log-normal distributions; iii) the Hong Kong stock market tends to follow the movement of the US stock market; iv) the Monday stock returns in Hong Kong tend to be lower and have higher volatility; v) the volatility of daily returns is persistent; vi) impact of economic shocks on stock market last longer than one day.

摘要

本論文研究恆生指數每分鐘回報率的極值(ExtremeValues).跟據Tsay在1999年的研究方法,本文集中研究一些超出特定值(thresholds)的回報率,並假定這些回報率的發生次數與及其超出特定值的幅度爲一個二維泊松過程(two-dimensional Poisson Process).

主要研究結果如下:

(一)香港股票市場的波動性在亞洲金融風暴過後顯著上升;

(二)每日與及每分鍾的回報不是對數正態分佈;

(三)港股傾向跟隨美股變動;

(四)香港股市在周一的回報率較其它交易日爲低,並有較高波動性;

(五)每日回報率的波動性是持久的;

(六)經濟衝激(economic shocks)對股市的影響是超過一日.

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# 1 Introduction

Large price movements like stock market booms and crashes are relatively rare, but these events are of great importance for investors and for the whole economy. Extreme fluctuations of stock prices are definitely undesirable because they may impair the smooth functioning of the financial system and adversely affect the performance of an economy.

Stock crashes such as those occurred during the Asian Financial Crisis could harm the economy through different channels. First, big drop in stock prices would reduce consumer spending through wealth effect. It may also weaken public confidence about the economy which consequently lowers consumption further. Secondly, stock price volatilities may have impacts on business investment spending. Investors may demand higher returns to compensate the higher risk in the stock market. Consequently, the cost for a firm to issue stock will be higher. Thirdly, big price changes could hinder the proper functioning of the financial system. Systems that function smoothly with normal price changes may not be able to deal with extreme price variations. Modifications in market rules or regulations may be needed to increase the flexibility of the system. For instance, after the October Crash in 1987, the Stock Exchange of Hong Kong underwent a complete reform, such as the establishment of a more widely representative Council to strengthen the market surveillance, see the website of Stock Exchange of Hong Kong, (http://www.sehk.com.hk) for details. Nevertheless, extreme price movements are not well understood by both practitioners and researchers. My study may shed some light on this issue.

In this thesis, I study the extreme values or tail behavior of stock returns in Hong Kong. Following Tsay (1999) I model the generating process of extreme values and relate the tail behavior of the process to economic variables. More specifically, I focus on observations that exceed some thresholds and on their associated exceedances. I assume that the exceedance times and the excess follow a two-dimensional Poisson process with a parametric intensity function. In view of asymmetric distribution of returns, positive and negative returns are handled separately.

The adopted approach not only provides a framework to investigate factors that affect the tail behavior of stock returns, it also gives information on the chance of exceedances and the magnitude of an excess. In other words, this approach enables us to examine whether the occurrence of large price movements has any patterns, and is related to the arrival of information or changes of economic variables. It also enables us to assess the downside risk of an asset and so on. With this approach, we can trace out factors that might have affected the tail behavior of stock returns. And these factors can be used to forecast large price changes (say 5%), similar to the stock market plunge during the 1997 Asian Financial Crisis, and thus reduce its adverse impacts to investors and to the whole economy.

The rest of this thesis is organized as follows. In section 2, I give a brief overview of the Hong Kong stock market. Section 3 presents the literature review. Section 4 discusses the methodology. Section 5 describes the data. Sections 6 and 7 present the empirical results of minute-by-minute and daily stock returns respectively. In section 8, I conclude.

# 2 Overview of Hong Kong Stock Market

In this section, I provide a brief description of the Hong Kong stock market and the history of Hang Seng Index. I will also discuss some factors that may affect stock price movements such as the influences of the US stock market and the Hong Kong government's intervention.

## 2.1 Stock Exchange of Hong Kong

Records of securities trading in Hong Kong date back to 1866. In 1891 when the Association of Stockbrokers in Hong Kong was established, Hong Kong had her formal stock market. It was renamed the Hong Kong Stock Exchange in 1914. In 1921, a second exchange was incorporated - the Hong Kong Stockbrokers' Association. The two exchanges merged to form the Hong Kong Stock Exchange in 1947. The rapid growth of the Hong Kong economy led to the establishment of three other exchanges in late 1960s and early 1970s, including the Far East Exchange (1969), the Kam Ngan Stock Exchange (1971) and the Kowloon Stock Exchange (1972). Subsequently, there were calls for the formation of a united stock exchange. As a result, the unified exchange — the Stock Exchange of Hong Kong — was incorporated on 7 July 1980. Trading on the Stock Exchange of Hong Kong finally commenced on April 2, 1986.[1]

Today, the Stock Exchange of Hong Kong is among the leading stock exchanges in the world. With market capitalisation of almost HK$4,945 billion as at the end of February, 2000, it ranks nineth in the world and second in Asia (behind Japan only). Many multinational fund management houses are paying more attention on the Hong Kong Market. It is

[1] Refer to the Stock Exchange of Hong Kong Limited, Fact Book 1999 for details.

gaining increasing influence in the world capital markets.[2]

Trading of the Stock Exchange of Hong Kong is conducted either through terminal in the trading hall of the Exchange or the off-floor trading terminals at member's offices. Trading is conducted on weekdays (excluding Saturdays and public holidays). There are two trading sessions, morning session (10:00a.m. to 12:30 p.m.) and afternoon session (2:30 p.m. to 4:00 p.m.).

## 2.2 Hang Seng Index

Hang Seng Index (HSI), the benchmark of the Hong Kong stock market, is one of the best known indices in Asia. It is the most widely quoted index of the Hong Kong stock market both locally and internationally. It is used by many fund managers as their performance benchmark.

Hang Seng Index was first published on November 24, 1969. The index series was back-dated to July 31, 1964 with a base value of 100. It is a value-weighted index (shares outstanding multiplied by stock price) of the 33 constituent stocks[3] which are representatives of the market. Table 1 presents the 33 constituent stocks of the Hang Seng Index as at June 2000. The aggregate market capitalization of these stocks account for about 70% of the total market capitalization on the Stock Exchange of Hong Kong Limited. The 33 constituent stocks are categorized into four sub-indices, i.e. Commerce and Industry, Finance, Properties and Utilities. Each constituent stock is weighted by its respective market capitalization so that the higher its market capitalization, the more influence it has with the index. The

[2]See to the website of Stock Exchange of Hong Kong (http://www.sehk.com.hk) for details.

[3]At base day there were only 30 constituent stocks.

constituent stocks of HSI has been changed 16 times since its introduction[4].

To meet the growing interests in the Hong Kong stock market and rising demand for related hedging tools, in May 1986, the Hong Kong Futures Exchange (HKFE) first introduced Hang Seng Index futures contracts. These contracts provide investors with a set of instruments to manage portfolio risk and to capture index arbitrage opportunities[5].

## 2.3 Influences of the United States

The Hong Kong economy is closely linked to that of the US. Since October 1983, the Hong Kong dollar has been linked to the US dollar at the rate of HK$7.80/US$1. The pegging of the Hong Kong dollar to the US dollar limits Hong Kong's monetary policy. This results in high correlation between interest rate patterns in the US and Hong Kong. Interest rate affects the cost of business investment and profitability of firms. So changes in interest rate have direct effect on the performance of an economy. Because of the co-movements of Hong Kong and the U.S. interest rate, Hong Kong's economic performance tends to follow the business cycle of the US. In addition, the US is Hong Kong's most important market for domestic exports. This trade relation further increases Hong Kong's dependence on the U.S. economically. These close links between Hong Kong and the U.S. imply that the Hong Kong Stock market and the U.S. may move together. However, because of the time difference (13 hours) between the U.S. and Hong Kong, a shock to the U.S. stock market at any day will have an effect, if any, to the Hong Kong stock markets in the following day.

[4] See Hang Seng Services Limited website (http://www.hsi.com.hk) for details.
[5] See Hong Kong Future Exchange website (http://www.hkfe.com) for details.

## 2.4 Hong Kong Government's Intervention

On Friday August 14, 1998, the Hong Kong government mount a massive and unprecedented HK$118.1 billion intervention in the stock market (that continued through the next two trading days August 17 and 18). The government acquired shares of the 33 Hang Seng Index constituent stocks.[6]

Since the start of Asian financial turmoil in October 1997, backed by reserves of US$60 billion, the linked exchange rate system of Hong Kong has withstood several attacks by international speculators.[7] However, the attack in early August apparently unnerved the government, forcing it to launched an counter-attack to "punish" speculators. The government believed that the speculators attempted to take advantage of the working of the peg exchange rate mechanism, to profit from short-selling shares and stock index futures. Under the system, pressure on the Hong Kong dollar exchange rate will invariably cause a contraction of Hong Kong dollar liquidity, which will drive up Hong Kong Interbank Offered Rates (HIBOR). The increase in interest rates almost certainly has an adverse effect in the stock markets. The increase in interest rates also enables short sellers to profit by buying shares at lower prices to settle their positions. Table 2 presents the figures of the government's market operation in August 1998. For instance, the government's shareholdings of Swire Pacific "A", New World Development and Cheung Kong Holdings, exceed 10% of these issued shares. The intervention greatly reduced the number of shares avaliable in the market.

This reduction in the stock availability may have made the stock prices more sensitive to change in supply and demand condition in the private sector (i.e. stock returns may be

[6]See the website http://www.info.gov.hk/gia/general/199810/26/1026191.htm for details.
[7]See the Hong Kong Monetary Authority (http://www.info.gov.hk/hkma), for example.

more volatile)[8].

In October 1998, Exchange Fund Investment Limited (EFIL) was established to manage the acquired portfolio. One of the duties of EFIL is to advise the Financial Secretary and the Hong Kong Monetary Authority on the disposal of the portfolio in an orderly manner. The initial method of disposal chosen by EFIL was through the issuance of Tracker Fund of Hong Kong (TraHK). On November 12, 1999, TraHK was listed on the Stock Exchange of Hong Kong.

[8]In the inhomogeneous model of daily returns, I have tried to include dummy for the period after government intervention. But the effects of this dummy are mixed and insignificant for various thresholds. Thus it is not included in the final model.

# 3 Literature Review

Many models have been introduced to account for the observed fat tails of stock returns distribution, though there is no consensus regarding the exact degree of distribution fatness and hence the generating process of the returns. On the other hand, the extreme values (or tail behavior) of stock returns receive relatively little spotlight. I summarize the related literature in this section.

## 3.1 Stable and Student $t$ Distributions

There has been a great debate whether stock returns follow a stable and Student $t$ distributions. Using daily data of the thirty stocks of the Dow-Jones Industrial Average from 1956 to 1958, Fama (1965) finds that the deviations from normality in the distributions of stock returns are in the direction predicted by the Mandelbrot hypothesis. A Gaussian model cannot explain these departures. In addition, he also illustrates that stock returns follow stable Paretian distributions[9] with characteristic exponents ($\alpha$) less than 2.

Blattberg and Gonedes (1974) employ daily data of 30 securities in the Dow-Jones Industrial Average between 1957 to 1962 and make a comparison of the stable Paretian and Student $t$ distributions[10], they find that the estimated degree of freedom $v$ in Student $t$

[9] The log characteristic function of a stable Paretian distribution with location parameter $\sigma$, scale parameter $c > 0$, and characteristic exponent $\alpha \in (0,2)$, is: $\ln\phi_{\bar{x}} = i\sigma t - |ct|^{\alpha}$,where $t$ is some real number and $i = \sqrt{-1}$. See Blattbergg and Gonedes (1974) for details.

[10] The Student $t$ density function with location parameter $m$, scale parameter $H$ >0, and degrees of freedom parameter, $v > 0$, is:

$f(x|m,H,v) = \frac{v^{\frac{1}{2}v}}{B(\frac{1}{2},\frac{1}{2}v)} \left[v + H(x-m)^2]^{-\frac{1}{2}(v+1)}\sqrt{H}\right]$,

where B $(\cdot,\cdot)$ is the "beta function", that is, $B(a,b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}$, where $\Gamma(\cdot)$ is the "gamma function." See Blattberg and Gonedes (1974) for details.

distribution and the characteristic exponent $\alpha$ in stable Paretian distribution increase significantly when period of return increases from 1 day to 5 days. The magnitude of this increase in the estimate of $v$ is found to be more consistent with the case of the Student $t$ model applied to data generated from Student $t$ model than the Student $t$ model applied to data generated from stable Paretian model. The increase in estimate of $\alpha$ suggests a unstable process, which is much closer to a process converging to normality. Furthermore, it is found that the values of the log-likelihood ratio of the 30 securities are greater than zero, indicating that the Student $t$ model provides a better description of the data than the stable Paretian model.

Jansen and de Vries (1991) apply extreme value theory to 6000 daily dividend compensated returns for ten stocks among the S&P 100 list, and two market indices in the US from 1962 to 1986. Specifically, they estimate the Paretian tail index directly from the tail observations (or extremes). They find that all tail-index estimates are between 3 and 5 and are significantly above 2 in 95% asymptotic confidence intervals. Thus there is empirical evidence supporting the Student $t$ and ARCH class distributions, instead of the stable class.

By Monte Carlo Simulation with 100 replications, McCulloch (1997) generates generalized Pareto (GP) tail-index estimates for a set of stable Paretian $\alpha$'s which range from 1 to 2. It is demonstrated that for $\alpha$'s between 1.65 and 2, the estimates calculated are all greater than 2 (i.e. they are upward-biased estimates of $\alpha$). Furthermore, he illustrates that if the distribution is truly stable, these tail index estimators would provide a highly unreliable estimate of stable $\alpha$ with the moderate sample sizes that were typically available. He finds that for $\alpha$ near or below 1, the Hill/Pareto tail-index estimates are quite stable and able to capture the Paretian behavior. Unfortunately, for higher values of $\alpha$, the estimates become entirely misleading — the estimate actually rises to infinity before $\alpha$ reaches 2. In at least one instance, this happens with $\alpha$ as low as 1.5. And this problem happens more often as $\alpha$ increases.

## 3.2 Generalized Distribution

Other distribution classes or models have been proposed for stock returns. For instance, Bookstaber and McDonald (1987) proposes a generalized distribution, called the generalized beta of the second kind (GB2) with one scale parameter and three shape parameters to describe security return. It contains a large set of common distributions as its special or limiting cases, such as lognormal, log-$t$ and log-Cauchy.[11] By selecting the value of parameters, distributions with different degree of fatness and large or even infinite higher moment can be generated. The authors show that GB2 can generalized the lognormal-gamma mixture employed by Praetz (1972). In addition, they demonstrate that under some restrictions GB2 will be closure under multiplication, i.e. if daily returns have one distribution, taking the product of these returns to generate longer period (say monthly) returns will lead to the same type of distribution function, though with different parameters. Finally, they apply bootstrap method to 500 daily return observations of twenty-one randomly chosen stocks respectively and fit the distribution of 1, 5, 25 and 250-day returns for each of the stocks. They find that for short period returns GB2 outperforms lognormal in fitting the sample data

[11]If $X = logY$ follows a Cauchy distribution, then $Y$ follows a log-Cauchy distribution. The density function of Cauchy has the form:
$f(x) = \frac{1}{\pi(1+x^2)}, -\infty < x < \infty$

but the reverse is true for long period returns. They point out that this result is consistent with other studies, such as Blattberg and Gonedes (1974).

## 3.3 Socio-economic Model

Another example is Lux (1998). By formalizing the transitions between chartist and fundamentalist strategies among speculators and the shifting between optimistic and pessimistic chartists, he establishes an socio-economic model of the interaction in financial market. He examines the time series generated by the model and finds that (i) there are waves of optimism and pessimism accompanied by deviations of the asset price from its fundamental value; (ii) the ratio of chartists increases during both optimistic and pessimistic waves and declines when the asset price reverts toward the fundamental value; (iii) there are recurring lead-lag relationships among share price, the ratio of chartists and the opinion index of non-fundamentalist traders. More importantly, he illustrates that the return distribution generated from this model possesses important features of financial data, specifically, fat-tailed. Also, he finds that the kurtosis decreases as the time span increases. This implication is consistent with the empirical finding that fatness of the distribution decreases when proceeding from daily to weekly and monthly data.

## 3.4 Extreme Value Analysis

We note that there are relatively few studies that focus directly on the extreme values. Notable exception is Longin (1996). He applies extreme value theory to investigate the extreme movements (i.e. estimates the asymptotic distribution of extremes) of the US stock index from 1885 to 1990 using both parametric and non-parametric approaches. The aforesaid asymptotic distribution of extremes contains three parameters. In the parametric approach (the maximum likelihood method and regression method), he estimates these parameters by assuming that the realized extremes are drawn exactly from the asymptotic distribution. In the non-parametric approach, he uses the method developed by Pickands (1975) and Hill (1975). Tail index is estimated from the stock index return series and is used for $t$-test to screen out the actual asymptotic distribution; he does not assume that extremes are drawn exactly from the asymptotic distribution. He finds (i) the asymptotic distribution of maximal and minimal returns is Fréchet distribution[12]; (ii) the distribution of returns are fat-tailed, in particular, the mean and the variance exist, while the skewness and the kurtosis, and all higher moments may be infinite; (iii) the asymptotic distribution is fairly stable over time; (iv) and the distribution of extremes is stable under time aggregation, the variation of returns length have little influence on it. Besides, he finds that the extremes tend to cluster: there are 28 years (out of 106) during which the minima and the maxima occur in the same week. However, he focuses on the maximum only, rather than on observations that exceed some high thresholds (the practice in modern methods of extreme value analysis).

Finally, none of the prior studies have related the tail behavior of generating process of extreme values to economic variables and handled positive and negative returns separately. Tsay (1999) fills the gap. He focuses on index returns (daily returns of S&P 500 index

[12] Fréchet distribution is defined as:

$$F_Y(y) = \begin{cases} 0 & \text{for } y \leq 0 \\ \exp(-y^k) & \text{for } y > 0 \text{ and } k > 0 \end{cases}$$

See Longin (1996) for details.

from 1962 to 1997) that exceeds some thresholds and on their associated exceedances, and assume that the exceedance times and the excess follow a two-dimensional process with a parametric intensity function. Besides, he deals with positive returns and negative returns separately. He finds that i) changes in U.S. daily interest rate have pronounced effects on the tails of index returns, ii) the tail behavior of index returns changes over time, iii) there is increasing chance of large excesses over high thresholds if exceedances occur, iv) there are more exceedances in the fourth quarter, v) there is asymmetry in daily returns of S&P 500 index.

Tsay's methodology has several advantages. First, the parameters of the two-dimensional Poisson process may be modeled as stable over time (i.e. homogeneous) or varying with time (i.e. inhomogeneous ). For inhomogeneous model, the parameters of the intensity function can be modeled to depend on explanatory variables. This framework is natural to study any trend in exceedance times and excess and to investigate factors that affect the tail behavior of security returns. Second, the model is widely applicable and easy to be estimated using either the maximum likelihood method or Markov Chain Monte Carlo methods. Third, the model provides information on both the chance of exceedances and the magnitude of an excess. Finally, several diagnostic tools are available to test the adequacy of an entertained model. In this thesis, I apply Tsay's methodology to stock returns in Hong Kong.

# 4 Methodology

I basically follow the approach originally introduced by Smith (1989), extended by Tsay (1999) to model financial time series. Tsay focuses on observations that exceed some thresholds. He uses homogeneous and inhomogeneous two-dimensional Poisson process to model the exceedance times and the excess of daily returns based on S&P 500 index. I apply this approach to Hang Seng Index minute-by-minute and daily data and handle the positive and negative returns separately. I try to explain the tail behavior of stock returns using the following variables: Dow Jones Industrial Average returns, volatility indicators, a Monday dummy, a time trend, the duration from the previous exceedance and an indicator for previous trading behavior.

The two-dimensional Poisson process is determined by an intensity function with three parameters $k$, $\sigma$ and $\mu$. The shape parameter $k$ determines tail behavior of the distribution. The case $k > 0$ yields distributions where there is a finite upper bound. The case $k = 0$ corresponds to distributions with exponentially declining tail, e.g. exponential, gamma, normal, lognormal, Weibull distributions. The case $k < 0$ gives heavy-tailed distribution. The location parameter $\mu$ shifts the distribution to the left or right, and hence determine its mean. And lastly, the scale parameter $\sigma$ stretches out or shrinks the distribution around $\mu$.

## 4.1 Homogeneous Model

For the homogeneous model, it is assumed that the exceedance times and values $(t_i, y_{t_i})$ are generated by a two-dimensional Poisson process with intensity function given by

$$\Lambda[(T_1, T_2) \times (y, \infty)] = \frac{(T_2 - T_1)}{T} G^c(y; k, \sigma, \mu), \tag{1}$$

where $G^c(y; k, \sigma, \mu) = (1 - \frac{k(y-\mu)}{\sigma})_+^{\frac{1}{k}}$, $T$ is the baseline time interval, the data span is $t = 1, ..., T^*$, the exceedance times of the threshold $r$ are represented by $t_i, i = 1, ..., N_r$, the observation at $t_i$ is $y_i$, $0 \le T_1 \le T_2 \le T^*$, $y > r$, $\sigma > 0$ and $\mu$ and $k$ are arbitrary real numbers.

Or equivalently,

$$\Lambda[(T_1, T_2) \times (y, \infty)] = \int_{T_1}^{T_2} \int_y^{\infty} \lambda(t, z) dz dt, \tag{2}$$

where $\lambda(t, y) = \frac{1}{t} g(y \; ; k, \sigma, \mu)$ and $g(.)$ is the derivative of $-G^c$ with respect to $y$ and $y > r$. The likelihood function of $\{(t_{1,} y_{t_i})\}$ over the set $[0, T^*] \times (r, \infty)$ is given by

$$L(k, \sigma, \mu) = \left( \prod_{i=1}^{N_r} \frac{1}{T} g(y_{t_i}; k, \sigma, \mu) \right) \times \exp\left[ -\frac{T^*}{T} G^c(r \; ; k, \sigma, \mu) \right]. \tag{3}$$

## 4.2 Inhomogeneous Model

Replacing the constant parameters $k$,$\mu$ and $\sigma$ by time dependent counterparts, we obtain the inhomogeneous model,

$$\Lambda\left[(0, T) \times (y, \infty)\right] = \left(1 - k_t \frac{y - u_t}{\sigma_t}\right)_+^{\frac{1}{k_t}}, y > r. \tag{4}$$

The likelihood function of $(t_i, y_{t_i})$ becomes

$$L = \left( \prod_{i=1}^{N_r} \frac{1}{T} g(y_{t_i}; k_{t_i}, \sigma_{t_i}, \mu_{t_i}) \right) \times \exp\left[ -\frac{1}{T} \int_0^{T^*} G^c(r; k_t, \sigma_t, \mu_t) dt \right]. \tag{5}$$

If one assumes that the parameters $k_t$, $\sigma_t, \mu_t$ are constant for each day, the likelihood function reduces to

$$L = \left( \prod_{i=i}^{N_r} \frac{1}{T} g\left(y_{t_i}; k_{t_i}, \sigma_{t_i} \mu_{t_i}\right) \right) \times \exp\left[ -\frac{1}{T} \sum_{t=1}^{T^*} G^c(r, k_t, \sigma_t, \mu_t) \right] \tag{6}$$

and the inhomogeneity of intensity function in this equation might be modeled as:

$$k_t = \beta_1' x_t, \ \ln(\sigma_t) = \beta_2' x_t, \ \mu_t = \beta_3' x_t \tag{7}$$

where $\beta_i$ are real-valued vectors and $x_t = (1, x_{1t}, ..., x_{st})'$ with explanatory variables $x_{jt}$, $j = 1, ..., s$.

In my study, I estimate the model by the maximum likelihood method. Tsay (1999) also uses the Markov Chain Monte Carlo method, in addition to the maximum likelihood method, to estimate the model. I choose not to do so to reduce computational burden.[13]

## 4.3 Model Validity

Checking the model used for exceedance times and excesses involves examining its three key characteristics[14]. First, it is to verify the adequacy of the exceedance rate. Second, it is to

[13]Tsay (1999) finds that his results from the Markov Chain Monte Carlo method and maximium likelihood method are similar.

[14]Please refer to Tsay (1999) for details

examine the distribution of excesses. Third, it is to check the independence assumption.

### 4.3.1 Exceedance Rate

For univariate Poisson process, we know that the time durations between two consecutive events are independent and follow exponential distribution. For a two-dimensional process model, Smith and Shively (1995) propose to examine the time durations between consecutive exceedances. If the two-dimensional Poisson process model is appropriate for the exceedance times and excesses, the time duration between the $i$-th and $(i-1)$-th exceedances should be exponentially distributed. More specifically, let $t_0 = 0$, we expect that

$$z_{t_i} = \int_{t_{i-1}}^{t_i} \frac{1}{T} g(y; k_s, \sigma_s, \mu_s) ds, i = 1, 2, ... \tag{8}$$

are independent and identically distributed (iid) as a standard exponential distribution. For discrete-time observations, i.e. minute-by-minute or daily returns, the time durations become

$$z_{t_i} = \frac{1}{T} \sum_{t=t_{i-1}+1}^{t_i} G^c(r, k_t, \sigma_t, \mu_t). \tag{9}$$

Then we use the quantile-to-quantile (QQ) plot to check the validity of the iid standard exponential distribution with mean one. If the model is adequate, the QQ-plot should show a straight line passing through the origin with slope one.

### 4.3.2 Distribution of Excesses

Under the two-dimensional Poisson process model, conditionally on $y_t > r$, the distribution of the excess $x_t = y_t - r$ over the threshold $r$ is generalized Pareto (GPD) with shape parameter $k_t$ and scale parameter $\psi = \sigma - k_t(r - \mu_t)$.[15] Therefore, we can make use of the relationship between a standard exponential distribution and GPD and define

$$w_{t_i} = \begin{cases} -\frac{1}{k_{t_i}} ln(1 - k_{t_i} \frac{y_{t_i} - r}{\psi_{t_i}})_+ & \text{if } k_{t_i} \neq 0 \\ \frac{y_{t_i} - r}{\psi_{t_i}} & \text{if } k_{t_i} = 0 \end{cases}. \tag{10}$$

If the model is adequate, $w_{t_i}$ should be independent and follow exponential distribution with mean one. We can then apply the QQ-plot to check the validity of the GPD assumption for excesses.

### 4.3.3 Independence

By examining the sample autocorrelation functions of time durations $z_{t_i}$ and excesses $w_{t_i}$, we can verify the independence assumption. Under the independence assumption, we expect zero serial correlations in both $z_{t_i}$ and $w_{t_i}$.

[15] Refer to Tsay (1999) for details.

# 5 Data

I perform the extreme value analysis on minute-by-minute and daily returns of the Hang Seng Index. The minute-by-minute data set covered minute-by-minute values of Hang Seng Index in every trading day from April 1, 1989 to March 31, 1999 which was purchased from HSI Services Limited. The daily data set contained daily closing value of Hang Seng Index returns from December 8, 1972 to March 3, 2000 and was obtained from the Datastream.[16] Using these two data sets, I compute their corresponding returns series, specifically, the return $y_t$ at time $t$ are defined as:

$$y_t = 100 \times (\frac{P_t}{P_{t-1}} - 1) \tag{11}$$

where $P_t$ is the value of the Hang Seng Index at time $t$.[17] I separate positive returns from negative one by considering exceedances for $y_t$ and $-y_t$ over the thresholds 1%, 1.5% and 2% for daily returns, and 0.025%, 0.05%, 0.075%, 0.1%, 0.125%, 0.15%, 0.175% and 0.2% for minute-by-minute returns. Note that the exceedances of $-y_t$ are for the negative tails of $y_t$. I do not investigate any threshold exceed 2% (or 0.2%) because exceedance times of higher thresholds have fewer observations and the estimation becomes difficult.

[16] Although the history of Hang Seng Index dated back to January 1, 1969, for the period from January 1, 1969 to December 7, 1972, there were no daily observations (the highest frequency of the data available were either monthly or weekly).

[17] For daily returns, the $P_t$ is the closing value of the Hang Seng Index at the $t$-th trading day.

## 5.1 Minute-by-minute Returns

For the minute-by-minute returns series, I analyze them by calendar year. There are several reasons for breaking down the data by year. First, separating the data by year reveals the variations of the characteristics of the stock market over time. Second, for high frequency data, observations within one year is adequately large for one to investigate the tail behavior of stock returns for various large thresholds. Third, the full data set is too large (more than four hundred thousand observations) and due to the fact that the models employed in this thesis are highly nonlinear, the estimation using the full data set will be very difficult and time consuming. Analysing the data by year reduces the computational burden.

Tables 3 and 4 report the summary statistics and exceedance times for the period covered respectively. The greatest magnitude for both positive and negative returns occurred in 1997, i.e. 8.09% and 11.82%. In 1989, despite a stock crash, there are only few exceedance times. Four out of the eleven years have negative sample mean returns, including the three years (1989, 1997 and 1998) with stock crashes. During the years of Asian Financial Crisis (i.e. 1997 and 1998), negative returns have more exceedances almost for all thresholds (except the two lowest thresholds). Thus it looks like that when the stock market falls, it falls hard and rapidly, but when the stock market rises, it rises slowly. This pattern suggests an asymmetry in the distribution of positive and negative returns. Year 1993, 1997 and 1998 peaked in the exceedance times for both returns, especially for 1997 and 1998. 1997 and 1998 have more than 600 exceedance times over the highest threshold 0.2%. 1991 and 1996 have the fewest exceedance times. For instance, in 1991, the number of exceedance times over the highest threshold (0.2%) is less than a hundred. The volatility of stock returns (as measured by standard deviation) after the Asian Financial Crisis. The standard deviations are all above 0.1 in 1997, 1998 and 1999. In contrast, year 1991 has the smallest standard deviation of 0.0452. This variation in exceedance times suggest that it may be worthwhile to analyze the data by subsamples (calendar years in my case).

## 5.2 Daily returns

For daily returns, I use daily closing value of Hang Seng Index returns from December 8, 1972 to March 3, 2000 to compute the daily returns series. Tables 5 and 6 report the summary statistics and exceedance times by quarters respectively. The sample mean and standard deviation of the daily return series are 0.0650% and 1.9662% respectively. The maximum and minimum returns over the sample period are 18.8237% (occurred on October 29, 1997) and -33.3305% (occurred on October 20, 1987) respectively. For high thresholds (2%), the first quarter and fourth quarter have more exceedance times.[18] The fourth quarter seems to be more volatile. Besides the occurrence of maxima, its sample standard deviation is the largest (2.2048), while that of other quarters are all below 2.

## 5.3 Explanatory Variables for the Inhomogeneous Model

I use the following variables in the inhomogeneous models to explain the tail behavior of stock returns:

1. The Dow Jones Industrial Average ($x_{1t}$): $x_{1t}$ is the Dow Jones Industrial Average return at time t-1. It is well known that Hong Kong has a tendency to follow stock

[18]The stock market of US also has more exceedance times over high thresholds in the fourth quarter.

price fluctuations in US, specifically New York Stock Exchange (see for instance, Aggarwal and Rivoli (1989a)). This variable is included to examine the effects of US stock market on that of Hong Kong.

2. Volatility indicators ($x_{2t}$, $x_{3t}$, $x_{4t}$ and $x_{5t}$) : $x_{2t}$ is the number of days during the previous 10 trading days with the absolute return exceeding the given threshold. $x_{3t}$, $x_{4t}$ and $x_{5t}$ are respectively the lagged 1-, lagged 2- and lagged 3-period squared returns of the Hang Seng Index. These four variables are used as a measure of recent market volatility. $x_{2t}$ measures the volatility for a longer time span (10 days) with an emphasis in intensity of the volatility, while $x_{3t}$, $x_{4t}$ and $x_{5t}$ reflect shorter time span (3 days) volatility and with an emphasis in the mangitude of the volatility. We suspect the more volatile is the previous trading days, the higher the chance of occurrence of extreme returns.

3. Monday dummy ($x_{6t}$): $x_{6t}$ equals to 1 if the trading day is Monday, equal to 0, otherwise. Previous studies (e.g Aggarwal and Rivoli (1989b), Fortune (1989), Kamara (1997), Pattel and Wolfson (1982), and Pennman (1987)) found strong evidences that Monday returns are significantly lower than those of other weekdays. In addition, some prior studies find that the volatility on Monday significantly differs from that of other weekdays (e.g. Fortune (1989), and Ho and Cheung (1994)). Following previous studies, I include this Monday dummy.

4. Time trend ($x_{7t}$): time trend is defined as $x_{7t} = year - 1971$, where "year" is the year to which the $t$-th daily return belongs. $x_{7t}$ is used to address the issue of whether there

exists a trend in exceedance times and excesses of the return series.

5. Indicator for the behavior of the previous trading day ($x_{8t}$): To investigate the possibility that a big change in the Hang Seng Index is followed by another big change but in the opposite direction, we set to $x_{8t}$ equal 1 if the return series considered at time $t-1$ exceeds the threshold, but in the opposite direction, and equal 0, otherwise.

6. Duration from the previous exceedance ($x_{9t}$): $x_{9t}$ is the number of trading days, inclusive, from the previous exceedance of the series under study, i.e. $y_t$ or $-y_t$. Many studies find that extreme returns tend to cluster, i.e. if there are many large observations in the past few days, it is more likely for observing a large observation in the coming few days.

I have also tried to include other variables. My choice of final model is based on the specification test to be discussed in section 7.2. I have tried to include Hong Kong interbank rates (HIBOR) in the models. However, the series is too short, no data is available prior to 1986. Preliminary analysis based on data after 1986 shows that the effects of HIBOR are insignificant. I have also tried to use US interest rate ( one year constant yield t-bill rate) as a proxy for interest rate in Hong Kong to explain the tail behavior. But the coefficients are found to be insignificant. In addition, I have tried to include the dummies for the period after October 1997 (the start of Asian Financial Crisis) and the period after the introduction of Hang Seng Index futures and in the models. But its effects are insignificant.

# 6 Empirical Results: Minute-by-minute Returns

In this section, homogeneous two-dimensional Poisson process is used to model the exceedance times and excesses for minute-by-minute Hang Seng Index returns. I choose T=240 as the base time interval which approximately equals to the number of daily trading minute. I do not consider inhomogeneous models for minute-by-minute Hang Seng Index returns because minute-by-minute observations for economic variables such as Dow Jones Industrial Average returns, interbank rate and T-bill rate are not available. We will consider inhomogeneous models only for daily returns.

## 6.1 Shape Parameter $k$

Tables 7 and 8 report the estimates of the shape parameter $k$ for positive and negative minute-by-minute returns respectively. The estimates of the shape parameter $k$ for both positive and negative returns are negative and highly significant (at 1% significant level). This suggests that the minute-by-minute stock returns in Hong Kong do not follow log-normal distribution but a distribution with non-decaying tails.

For both positive and negative returns, the estimates of the shape parameter $k$ vary drastically across different thresholds. Figure 1 plots the estimates of the shape parameter $k$ for the years covered against thresholds. The curves obtained are downward sloping for both positive and negative returns (except for several years over very high thresholds, i.e. $r$ greater than 0.15%), it indicates that the estimates of the shape parameter $k$ decrease (become more negative) with thresholds. In other words, the magnitude of estimates of the shape parameter $k$ increases with thresholds. This suggests that the location close to the end of tails deviates more from lognormal distribution.

Figure 2 plots the estimates of the shape parameter $k$ for all the thresholds considered against time. It is noted that three set of time trends are found among the threshold considered for both positive and negative returns, i.e. the time trends for low thresholds (0.025% and 0.05%), for intermediate thresholds (0.075% to 0.15%) and high thresholds (0.175% and 0.2%) respectively.

## 6.2 Location Parameter $\mu$

Tables 9 and 10 report the estimates of the location parameter $\mu$ for positive and negative returns respectively. All estimates of the location parameter $\mu$ are highly significant. The estimates of the location parameter $\mu$ are stable across different thresholds. This suggest that the means of the various thresholds considered are rather close.

Figure 3 plots the estimates of the location parameter $\mu$ for all years considered against thresholds for positive and negative returns respectively. The curves are almost horizontal lines, indicating the stability of estimates across thresholds. The estimates of location parameter $\mu$ for both positive and negative returns and for all thresholds considered in recent years, i.e. 1997, 1998 and 1999, are much greater than the earlier years (see rows 11 to 13 of 9 and 10). For instance, during the aforesaid period, all estimates are higher than 0.3 with highest value 0.3820 and 0.3777 for positive returns (at the threshold 0.1%) and negative returns (at the threshold 0.1%) respectively.

Figure 4 plots the estimates of the location parameter $\mu$ against sample time for positive and negative returns. It is noted that for both positive and negative returns, the estimates of the location parameter $\mu$ share similar upward trends across all thresholds. The similarity of the trends for the estimates for positive and negative returns suggests a year with high conditional mean in the distribution of positive returns is likely associated with high conditional mean (in absolute value) in the distribution of negative returns. This upward trend of the location parameter $\mu$ estimates for the positive and negative returns suggests that the market has become more volatile in recent years.

## 6.3 Scale Parameter $\sigma$

Tables 11 and 12 report the estimates of the scale parameter $\sigma$ for positive and negative returns respectively. All estimates of the scale parameter $\sigma$ are highly significant. However, estimates are less stable than estimates of the location parameter $\mu$, especially for the years of 1995 and 1998. Figure 5 plots the estimates of the scale parameter $\sigma$ for all years considered against thresholds for positive and negative returns respectively. The resulting curves are slightly upward sloping, suggesting the estimates of the scale parameter $\sigma$ increase with thresholds for both positive and negative returns.

Figure 6 plots the estimates of the scale parameter $\sigma$ of different thresholds against time for positive and negative returns. Similar upward trends are found for all thresholds and for both positive and negative returns. I note that the trends for estimates of the scale parameter $\sigma$ are very similar to those estimates of the location parameter $\mu$. The upward trends in both scale parameter $\sigma$ and location parameter $\mu$ indicate the conditional volatility of stock market is increasing over time. There is a big jump in the estimates of the scale parameter $\sigma$ in 1997 (Asian Financial Crisis) and those estimates of the scale parameter $\sigma$

remain high afterwards. Thus there is a rise in volatility of the Hong Kong stock market after 1997.

Two events might explain this increase in volatility in the Hong Kong stock market after 1997. First, 1997 marked the year of Asian Financial Crisis. In this year, Hong Kong's stock market was adversely affected very much. For instance, the index fell dramatically for four consecutive trading days through October 20 to October 23, 1997. Second, in 1998, to defend the attacks from international speculators, the Hong Kong government supports stock price by buying HSI constituent stocks from the market.[19] This reduction in the stock availability in the market might have made the stock price more sensitive to change in supply and demand conditions in the private sector. Therefore, volatility is seen to be higher.

## 6.4 Conditional Scale Parameter $\psi$

By defining $\psi = \sigma - k(r - \mu)$, we can obtain widely used conditional distribution function for excess over the threshold $r$,[20] which is known as Generalized Pareto Distribution

$$Pr(X \leq r + x | X > r) \approx G(x; \psi, k) = \begin{cases} 1 - (1 - kx/\psi)_{+}^{\frac{1}{k}} & \text{if } k \neq 0 \\ 1 - \exp(-x/\psi) & \text{if } k_{t_i} = 0 \end{cases} \tag{12}$$

where $(y)_{+}$=max($y$,0), $\psi > 0$, $0 \leq x < \infty$ if $k \leq 0$, and $0 < x < \psi/k$. Tables 13 and 14 report the computed $\psi$'s for positive and negative returns repectively. $\psi$'s are much less stable across thresholds than estimates of $\mu$, especially for thresholds greater than 0.15%.

[19]The Hong Kong government purchased shares of the 33 component stocks of Hang Seng Index in August 1998, see section 2.

[20]Refer to Tsay (1999) for details.

Figure 7 plots $\psi$'s for the 11 years investigated against thresholds for positive and negative returns. The curves formed are only slightly upward sloping for thresholds less than 0.15% but become steeper for thresholds beyond this value (except in 1993, $\psi$ decrease slightly with thresholds). This suggests that $\psi$ increases exponentially with thresholds for both positive and negative returns. Figure 8 plots $\psi$'s of all the thresholds considered against time. Two time trends are observed for these thresholds, one for thresholds from 0.025% to 0.125% and the other for thresholds from 0.15% to 0.20%. This indicates that the stock returns conditional on high and low thresholds behave in a very different way over time. In other words, different levels of returns are likely influenced by different factors.

Using $\psi$'s computed from the formula $\psi$=$\sigma$-$k(r$-$\mu)$ and the estimates of the shape parameter $k$, I plot the corresponding conditional distribution functions (Generalized Pareto Distribution) of excesses for both positive and negative returns. Figures 9 and 10 show the conditional distribution functions of excesses across different thresholds for positive and negative returns respectively. The curves of conditional distribution functions of the year with a stock crash (i.e.1989 and 1997) for both positive and negative returns over all thresholds considered are bounded by those of other years (except for negative returns over thresholds 0.125% and 0.15%). This result is different from our expectation that the year with stock crash should be more volatile than those years without crash. Thus the conditional distribution functions of these years should converge to 1 at slower speed than the other years. I also note that the curves of conditional distribution functions over thresholds 0.175% and 0.20% are much more unstable over time than those of other thresholds considered for both positive and negative returns.

Figures 11 to 21 plot the conditional distribution functions for the 8 thresholds considered in the same graph for all the years analyzed. It is noted that the conditional distributions for low thresholds converge to 1 faster than those of high thresholds (except for 1993). In particular, for all years (except 1993), the lowest threshold 0.025% is the fastest converging to 1 (the star line), while the highest threshold 0.20% is the slowest converging to 1 (the dotted line). It is observed that the conditional distribution functions of 1993 and 1999 are much more stable over thresholds than those of other years for both positive and negative returns (see figures 15 and 21), whereas those of 1995 and 1996 are much more unstable over thresholds (see figures 17 and 18).

### 6.5 Specification Test

In general, the diagnostic statistics, i.e. QQ-plots and autocorrelation plots (figures are not reported), suggest that the models are not so adequate. But both QQ-plots and autocorrelation plots for time durations $z_{t_i}$ and excesses $w_{t_i}$ show that when moving from low to high thresholds, there are improvements. The QQ-plots for high thresholds are closer to the target line of a standard exponential distribution than those for low thresholds. The autocorrelation plots show that the serial correlations for high thresholds are smaller than those for low thresholds. For thresholds (greater than 0.15%), the models are fairly adequate.

## 7 Empirical Results: Daily Returns

In this section, I report the analysis results for daily returns in separate subsections, one for homogeneous model and the other for inhomogeneous model. I use T=22 as the basic time period which corresponds approximately to the number of trading day in a month.[21]

## 7.1 Homogeneous Model

In this subsection, I use a homogeneous two-dimensional Poisson process to analyse the daily Hang Seng Index. Table 15 presents estimation results. Similar to the case of minute-by-minute returns, all estimates of shape parameter $k$ are negative and highly significant (at least at 1% significant level). This result suggests that the daily stock returns in Hong Kong do not follow log-normal distribution but a distribution with non-decaying tails. For all thresholds, the estimates of shape parameter $k$ for positive returns are more negative than those of negative returns. This is consistent with the fact that positive returns have more exceedance times than those of negative returns. In general, the magnitude of estimates of the shape parameter $k$ increases with thresholds. This finding indicates that the location close to the end of tails deviates more from log-normal distribution. The estimates of the shape parameter $k$ vary remarkedly across thresholds. There are large difference between the estimates of the shape parameter $k$ for positive and negative returns. This suggests the distribution of the stock returns in Hong Kong is asymmetric. The estimates of the location parameter $\mu$ are stable across thresholds for both positive and negative returns. This result suggests that the mean is rather close across thresholds. The estimates of the scale parameter $\sigma$ are less stable than those of the location parameter $\mu$ but more stable than that of the shape parameter $k$. This finding shows that the volatility is less stable across thresholds.

[21] The selection of T does not affect estimation result, the estimates of shape parameter $k$ and the conditional distribution distribution function remains unchanged for different T. However, it can affect the speed of convergence.

Figures 22, 23 and 24 show the QQ-plots for time durations $z_{t_i}$ and excesses $w_{t_i}$ for both positive and negative returns over thresholds 1%, 1.5% and 2% respectively. The dash lines represent the ideal target that passes through the origin with slope one. The QQ-plots of the time durations $z_{t_i}$ series exhibit some nonlinearity (see panels (a) and (c) of the figures for details).

Figures 25, 26 and 27 present the autocorrelation plots for time durations $z_{t_i}$ and excesses $w_{t_i}$ for both positive and negative returns over thresholds 1%, 1.5% and 2% respectively. The two dash lines in the figures are the asymptotic two standard error bounds. Both the time duration $z_{t_i}$ and excesses $w_{t_i}$ show some serial correlations. Thus, the diagnostic statistics suggest that the homogeneous models are inadequate.

## 7.2 Inhomogeneous Model

In this subsection, I consider inhomogeneous model and check whether allowing shape parameter $k$, location parameter $\mu$ and scale parameter $\sigma$ to varying with some financial indicators will improve the model's goodness of fit and its adequacy.

Tables 16 to 18 summarize the estimation results over thresholds 1%, 1.5% and 2% respectively. The inhomogeneous models perform much better than homogeneous models. For all thresholds considered, the maximized log-likelihood value increases dramatically (number not reported) relative to the homogeneous model. Likelihood ratio tests support the inhomogeneous models against homogeneous models (at 5% level of significance, not reported in the table). Figures 28, 29 and 30 show the QQ-plots for time durations $z_{t_i}$ and excesses $w_{t_i}$ for both positive and negative returns over thresholds 1%, 1.5% and 2% respectively. For both positive and negative returns and over all thresholds, the QQ-plots for time durations $z_{t_i}$ and excesses $w_{t_i}$ are much closer to the target line of a standard exponential distribution.

Figures 31, 32 and 33 present the autocorrelation plots for time durations $z_{t_i}$ and excesses $w_{t_i}$ for both positive and negative returns over thresholds 1%, 1.5% and 2% respectively. It is noted that serial correlations are much smaller than those of the homogeneous models, with only minor correlations for some thresholds. In general, the diagnostic statistics indicate that the estimated inhomogeneous models are adequate, especially for positive returns. In the following subsections, I discuss the estimated models in details.

Note that variables in the final model are chosen based on their contribution on the model adequacy test as well as their statistical significance. Because the final model is achieved after an extensive model selection procedure, our discussion of statistical significance have to be taken with a grain of salt.

### 7.2.1 Constant Term

For both positive and negative returns, all constant estimates (except positive returns over the thresholds 1%) of the shape parameters $k_t$ across all thresholds are statistically not different from zero even at 10% significant level (referring to the first row of tables 16 to 18). The insignificance of the shape parameter $k_t$ says that without external interventions such as economic shocks the distribution of the stock returns in Hong Kong has exponentially decaying tails.

### 7.2.2 Dow Jones Industrial Average Returns

As discussed in the data section, previous studies find that Hong Kong stock market tends to follow stock price movements in the U.S.. This variable is included to investigate the effects of the U.S. stock market on that of Hong Kong. The effect of Dow Jones Industrial Average Returns ($x_{1t}$) on the tail behavior or extreme values is statistically significant at the 5% level for both positive and negative returns for all thresholds studied (the second row of tables 16 to 18). For positive returns, it significantly affects all three parameters, except for scale parameter $\sigma_t$ over the threshold 1.5%. For negative returns, at the threshold 2.0%, it significantly affects all three parameters, whereas at relatively low thresholds (i.e. 1% and and 1.5%), it affects the location $\mu_t$ and shape parameters $\sigma_t$ only. It is interesting to note that the coefficients for all three parameters are positive for positive returns and negative for negative returns. The positive coefficients for location parameter $\mu_t$ of positive returns and the negative coefficients for location parameter $\mu_t$ of negative returns suggest that high stock returns in the US is associated with large location parameter $\mu_t$ for positive returns and small location parameter $\mu_t$ for negative returns.

Note that I investigate the negative tail of $y$ by considering $-y_t$ series over different thresholds. A small location parameter $\mu_t$ for negative returns should be interpreted as less negative conditional means, i.e. higher conditional means. Hence, the conditional means of the stock returns in Hong Kong are positively related to stock returns in the US. Similarly, the opposite sign of coefficients for shape parameter $k_t$ for positive and negative returns, implies that fatness of tails are negatively related to stock returns in the US . The positive and significant coefficients of the scale parameter $\sigma_t$ for positive returns suggest that volatility of positive returns in Hong Kong increases with stock returns in the US, the opposite is true for negative returns. The above results suggest that the price movements of the US stock market significantly affects the tail behavior of stock returns in Hong Kong. In particular, stock returns in Hong Kong are positively correlated with those of the US market. This result is consistent with previous findings that Hong Kong's stock market tends to follow the movements in the US (e.g. Aggarwal and Rivoli (1989a)).

### 7.2.3 Volatility Indicators

To see the effects of past volatility on the distribution of stock returns, I include a simple volatility measure (the number of days during the previous 10 trading days with the absolute returns exceeding the given threshold ($x_{2t}$)) similar to Tsay (1999)[22] and the lagged squared returns ($x_{3t}$, $x_{4t}$ and $x_{5t}$) in my models. I find that for the case of daily stock returns in Hong Kong, the inclusion of the lagged squared returns are necessary for model validity. Inclusion of the lagged squared returns reduces serial correlation in the time duration $z_{t_i}$ and excesses $w_{t_i}$ (Figures 31 to 33). In any case, results are similar to those of Tsay. As in Tsay (1999), I find that $x_{2t}$ is statistically significant in the location parameter $\mu_t$ and the scale parameter $\sigma_t$ for both positive and negative returns across all thresholds (the third row of tables 16 to 18). All the coefficients of $x_{2t}$ for the location parameter $\mu_t$ and the scale parameters $\sigma_t$ are positive.

The effects of the squared lagged returns ($x_{3t}$, $x_{4t}$ and $x_{5t}$) appear to be statistically significant in the location parameter $\mu_t$ and the scale parameters $\sigma_t$ (significant at 1% level)

[22]Note that Tsay (1999) use the number of days during the previous five trading days instead of ten.

for both positive and negative returns (the fourth to sixth rows of tables 16 to 18). In addition, the estimated coefficients of the lagged squared returns across all thresholds for the location parameter $\mu_t$ and the scale parameter $\sigma_t$ are positive as well. The positive coefficients of these four variables for scale parameter $\sigma_t$ suggest that if the stock market was volatile in the past few days, then the market is more likely to be volatile today, i.e. conditional volatility or variance is persistent (or clustering). This result is consistent with previous studies that conditional variance of stock returns tends to be persistent (e.g. Harvey and Siddique (1999), among others). This provides evidence that the effects of news or economic disturbances last longer than one day. For positive returns, the positive coefficients for the location parameter $\mu_t$ suggest that high volatility is associated with high conditional mean. For negative returns, the positive coefficients for the location parameter $\mu_t$ suggest the high volatility is associated with a more negative conditional mean.

### 7.2.4 Monday Dummy

I also include Monday dummy ($x_{6t}$) because there is evidence that Monday stock returns and volatility differ from those of other weekdays. The Monday effect[23] is present mainly in negative returns (the seventh row of tables 16 to 18).[24] For positive returns, there is no evidence of Monday effect, whereas for negative returns, the effect is on all three parameters for all thresholds. There are many explanations for the presence of Monday effect. For instance, firms may tend to release bad news during weekend, which results in lower returns

[23]Some authors such as Fortune (1999), refer it as weekend effect

[24]I have also tried including day-of-the-week effect, January effect as well as fourth quarter dummy. I do not include them in the model becasue they are insignificant statistically and their absence will reduce the computational burden.

but higher volatility on Mondays (e.g. Pattel and Wolfson (1982) and Pennman (1987)). The positive coefficients of the scale parameter $\sigma_t$ for negative returns suggest that the volatility on Monday is usually higher. The statistically insignificant coefficients of the scale parameter $\sigma_t$ for positvie returns suggests that Monday effect does not affect the volatility of positive returns. Thus, we have the overall effect that the stock volatility in Hong Kong is higher on Monday. This finding is consistent with the findings reported by Ho and Cheung (1994) and Aggarwal and Rivoli (1989b). The positive and significant coefficients for negative returns suggest that the conditional mean of negative returns is lower on Monday. The insignificant coefficients of the location parameter $\mu_t$ for positive returns suggest that Monday effect does operate on conditional mean. Thus, the stock returns in Hong Kong are often lower on Monday. This finding is consistent with previous studies on Monday Seasonal (e.g. Kamara (1997) and Wilson and Jones (1993)). The lower returns and higher volatility suggest that investors are not compensated for taking higher risk on Monday.

### 7.2.5 Time Trend

Similar to Tsay's findings about the daily returns of S&P 500, I find that the tail behavior of daily returns of Hang Seng Index evolves over time. Tsay finds that the evolution of the tail behavior of S&P 500 is mainly occurred in negative returns, whereas I find that the variation of the tail behavior of Hang Seng Index is mainly occur in positive returns.

For positive returns, there is evidence of decreasing time trends for location $\mu_t$ and scale parameters $\sigma_t$ and increasing time trend for shape parameter $k_t$ (the eighth row of tables 16 to 18). This indicates that the conditional mean and volatility for positive returns are decreasing over time, while the tail is becoming thinner over time. For negative returns, there is a positive time trend in the scale parameter $\sigma_t$ across all thresholds. This suggests the conditional mean (in absolute value) for negative returns is increasing over time, i.e. becoming more negative. However, for the other two parameters, time trend appears in the thresholds 2% only .

### 7.2.6 Duration Dummy

For positive returns, the effects are significant on the scale parameter $\sigma_t$ over the thresholds 1.5% only (the ninth row of tables 16 to 18). This is different from Tsay's results, he finds that the duration dummy significantly affects the location parameter $\mu_t$ across all thresholds. My results for negative returns is similar to Tsay's, the impacts of duration dummy ($x_{8t}$) mainly appear in the location parameter $\mu_t$ but they are present across all thresholds. The duration dummy ($x_{8t}$) may represent two possible effects. First, if the news arrival is random, longer period should contain more news. As variations of stock price are originated from news arrival, the longer the duration from the previous exceedances, the greater chance for observing a big price change, and have high conditional mean for positive returns and low conditional mean for negative returns. Hence, the sign of the coefficients of the duration dummy for location parameter $\mu_t$ should be positive. Second, impacts of news may last more than one day, i.e. stock returns clusters. This implies that conditional means of positive returns and the $-y_t$ series should be negatively related to duration from the the previous exceedance, i.e. the coefficient should be negative. The negative coefficients for location parameter for negative returns suggest the second effect dominates, whereas the positive coefficients for scale parameter $\sigma_t$ for positive returns suggest that first effect dominates.

### 7.2.7 Indicator for the Behavior of the Previous Trading Day

The indicator for exceedances over the threshold one trading day earlier but in the opposite direction ($x_{9t}$) significantly affects the tail behavior of both positive and negative returns for all thresholds considered (the tenth row of tables 16 to 18). On the contrary, Tsay finds that the $x_{9t}$ has effects on the location parameter $\mu_t$ for negative returns of S&P 500 over the thresholds 1% and 1.5% only. Except for returns over the threshold 1% all coefficients are positive. This result suggests that a big change in the daily Hang Seng Index is likely followed by another big change in the opposite direction. This indicates that Hong Kong stock market is rather volatile and substantial fluctuations are not rare. A probable explanation is investors overreact to some news or shocks. This finding provides some evidence that Hong Kong as an emerging market is more volatile (e.g. Bekaert and Harvey (1997)).

# 8 Conclusion

I have used both homogeneous and inhomogeneous two-dimensional Poisson process to model exceedance times and excesses over some high thresholds for both minute-by-minute (from April 1, 1989 to March 31, 1999) and daily (December 8, 1972 to March) Hang Seng Index returns. First, I find that the volatility of the Hong Kong stock market is higher for after the Asian Financial Crisis period. Second, my results suggest that both daily and minute-by-minute returns of the Hang Seng Index are asymmetric and do not follow log-normal distribution. The degree of deviation from log-normal distribution of the stock returns distribution is greater for the location close to the end of tails. Third, there is strong evidence that the Hong Kong stock market tend to follow the movement of the US stock market. Another finding is that the Monday stock returns in Hong Kong are lower and with higher volatility. It seems that investors are not compensated for taking higher risk. In addition, the volatility of daily returns is persistent. Finally, my results suggest that the impact of economic shocks on stock market last longer than one day.

Table 1: HSI Constituent Stocks

| | | |
|---|---|---|
| Amoy Property | First Pacific | Johnson Electric Holdings Ltd. |
| Bank of East Asia | Great Eagle Holdings | New World Development |
| Cable and Wireless HKT Ltd. | Hang Lung Development | Shanghai Industrial Hldgs |
| Cathay Pacific | Hang Seng Bank | Shangri-La Asia |
| Cheung Kong | Henderson Investment | Sino Land |
| China Resources | Henderson Land | S H K Property |
| China Telecom | HK Electric | SmarTone Telecom Hldgs Ltd. |
| CITIC Pacific | HK Gas | Swire Pacific (A) |
| CKI Holdings | HSBC Holdings | TV Broadcasts |
| CLP Holdings | Hutchison Whampoa | Wharf |
| Dao Heng Bank Group Ltd. | Hysan Development | Wheelock |

Note:

1. The constituent stocks were effective from December 6, 1999.

Table 2: Hong Kong government's shareholding of HSI constituent stocks after its 1998 intervention in stock market.

| Constituent Stock | No. of shares | % of Issued Shares |
|---|---|---|
| HSBC HOLDINGS PLC | 237,001,800 | 8.80% |
| HONG KONG TELECOM | 972,098,400 | 8.16% |
| HUTCHISON WHAMPOA | 304,550,000 | 7.86% |
| CHINA TELECOM | 478,806,000 | 4.06% |
| CLP HOLDINGS LTD | 136,022,000 | 5.50% |
| HANG SENG BANK | 109,202,700 | 5.71% |
| CHEUNG KONG HOLDINGS | 237,628,500 | 10.34% |
| SUN HUNG KAI PROPERTIES | 191,660,000 | 8.01% |
| HONG KONG ELECTRIC | 124,335,500 | 6.15% |
| HENDERSON LAND | 85,349,000 | 4.96% |
| HONG KONG CHINA GAS | 289,041,000 | 6.67% |
| CHEUNG KONG INFRAS | 96,403,000 | 4.28% |
| SWIRE PACIFIC 'A' | 115,433,000 | 12.28% |
| CITIC PACIFIC | 146,713,000 | 6.90% |
| CATHAY PACIFIC AIRWAYS | 119,208,000 | 3.52% |
| NEW WORLD DEVELOPMENT | 236,470,000 | 11.91% |
| WHARF HOLDINGS | 121,679,000 | 5.30% |
| HENDERSON INVESTMENTS | 91,308,000 | 3.24% |
| BANK OF EAST ASIA | 83,017,600 | 6.10% |
| AMOY PROPERTIES | 71,135,500 | 2.49% |
| SHANGHAI INDUSTRIAL HLDG | 71,413,000 | 8.49% |
| CHINA RESOURCE ENTERPRISES | 136,414,000 | 8.78% |
| HANG LUNG DEVELOPMENT | 33,156,000 | 2.50% |
| SHANGRI-LA ASIA | 61,674,000 | 3.44% |
| WHEELOCK & CO | 62,391,000 | 3.08% |
| SINO LAND CO | 107,238,000 | 3.43% |
| TELEVISION BROADCAST | 35,741,000 | 8.56% |
| FIRST PACIFIC | 143,864,000 | 6.07% |
| HYSAN DEVELOPMENT CO | 60,524,000 | 5.89% |
| HK & SHANGHAI HOTEL | 57,494,000 | 4.97% |
| HOPEWELL HOLDINGS | 209,323,000 | 4.78% |
| GREAT EAGLE | 24,652,000 | 4.51% |
| GUANGDONG INVESTMENT | 157,472,000 | 6.33% |

Note:

1. Now the portfolio is being managed by Exchange Fund Investment Limited (EFIL).
2. Sources: http://www.info.gov.hk/gia/general/199810/26/1026191.htm

Table 3: Summary statistics of minute-by-minute Hang Seng Index returns by year from September 3, 1989 to March 31, 2000.

| Years | sample size | mean | standard deviation | minimum | maximum |
|---|---|---|---|---|---|
| 89 | 42656 | -0.0002 | 0.0702 | -3.6744 | 1.1908 |
| 90 | 52660 | 0.0001 | 0.0488 | -1.0481 | 1.4537 |
| 91 | 52801 | 0.0007 | 0.0452 | -0.9641 | 2.5572 |
| 92 | 52933 | 0.0005 | 0.0675 | -2.3003 | 3.7851 |
| 93 | 52160 | 0.0015 | 0.0768 | -4.0681 | 3.6304 |
| 94 | 53908 | -0.007 | 0.0746 | -2.1346 | 2.0637 |
| 95 | 56104 | 0.0004 | 0.0512 | -1.5089 | 1.5045 |
| 96 | 58324 | 0.0005 | 0.0514 | -2.9786 | 2.3588 |
| 97 | 57405 | -0.0003 | 0.1178 | -8.0884 | 11.8170 |
| 98 | 58774 | 0.0000 | 0.1251 | -7.6487 | 6.0127 |
| 99 | 14309 | 0.0007 | 0.1023 | -2.1690 | 3.4334 |

Note:

1. Observations are grouped by calendar years.
2. For year 89, the observations from April to December only.
3. For year 99, the observations from January to March only.

Table 4: Exceedance times of minute-by-minute Hang Seng Index returns from 1989 to 2000.

| Years | | Thresholds | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 0.025% | 0.05% | 0.075% | 0.1% | 0.125% | 0.15% | 0.175% | 0.2% |
| 89 | positive | 9326 | 5011 | 2557 | 1439 | 805 | 506 | 339 | 224 |
| | negative | 9031 | 4815 | 2506 | 1460 | 794 | 469 | 308 | 214 |
| 90 | positive | 9532 | 4786 | 2375 | 1461 | 743 | 414 | 241 | 139 |
| | negative | 9323 | 4694 | 2359 | 1451 | 740 | 404 | 248 | 150 |
| 91 | positive | 9949 | 4399 | 2183 | 1027 | 488 | 249 | 134 | 83 |
| | negative | 9515 | 4214 | 2055 | 927 | 431 | 240 | 141 | 95 |
| 92 | positive | 14084 | 8094 | 4442 | 2698 | 1505 | 841 | 502 | 283 |
| | negative | 13717 | 7984 | 4357 | 2596 | 1497 | 823 | 475 | 275 |
| 93 | positive | 15106 | 9260 | 5999 | 3581 | 2004 | 1124 | 650 | 381 |
| | negative | 14360 | 8730 | 5700 | 3356 | 1784 | 953 | 566 | 316 |
| 94 | positive | 12952 | 7500 | 4166 | 2500 | 1561 | 990 | 635 | 428 |
| | negative | 13066 | 7675 | 4376 | 2647 | 1702 | 1085 | 726 | 483 |
| 95 | positive | 10075 | 4877 | 2409 | 1105 | 545 | 315 | 205 | 153 |
| | negative | 9893 | 4697 | 2311 | 1030 | 549 | 309 | 192 | 139 |
| 96 | positive | 11265 | 5212 | 2289 | 1020 | 521 | 287 | 191 | 133 |
| | negative | 11010 | 5067 | 2149 | 938 | 460 | 253 | 162 | 99 |
| 97 | positive | 15960 | 9434 | 5868 | 3706 | 2233 | 1421 | 950 | 656 |
| | negative | 15518 | 9348 | 5876 | 3777 | 2366 | 1566 | 1081 | 792 |
| 98 | positive | 18171 | 11753 | 7845 | 5265 | 3522 | 2328 | 1570 | 1069 |
| | negative | 18223 | 11914 | 7993 | 5425 | 3574 | 2365 | 1572 | 1101 |
| 99 | positive | 4012 | 2412 | 1590 | 1113 | 784 | 475 | 303 | 200 |
| | negative | 3927 | 2343 | 1585 | 1112 | 754 | 468 | 287 | 194 |

Note:

1. See notes in table 3

Table 5: Summary statistics of daily Hang Seng Index returns from December 8, 1972 to March 3, 2000.

| returns | sample size | mean | standard deviation | minimum | maximum |
|---|---|---|---|---|---|
| All | 7106 | 0.0650 | 1.9662 | -33.3305 | 18.8237 |
| Q1 | 1785 | 0.1273 | 1.9993 | -13.3080 | 14.4130 |
| Q2 | 1755 | 0.0681 | 1.857 | -21.7450 | 13.2040 |
| Q3 | 1775 | -0.0276 | 1.7709 | -9.4040 | 11.7140 |
| Q4 | 1791 | 0.915 | 2.2048 | -33.3305 | 18.8237 |

Note:

1. All: All observations from December 8, 1972 to March 3, 2000
2. Q1: Observations in the first quarters from December 8, 1972 to March 3, 2000
3. Q2: Observations in the second quarters from December 8, 1972 to March 3, 2000
4. Q3: Observations in the third quarters from December 8, 1972 to March 3, 2000
5. Q4: Observations in the fourth quarters from December 8, 1972 to March 3, 2000

Table 6: Exceedance times of daily Hang Seng Index returns for various thresholds considered from December 8, 1972 to March 3, 2000.

| | Positive Returns | | | Negative Returns | | |
|---|---|---|---|---|---|---|
| returns | $r = 1\%$ | $r = 1.5\%$ | $r = 2\%$ | $r = 1\%$ | $r = 1.5\%$ | $r = 2\%$ |
| All | 1642 | 1072 | 707 | 1378 | 944 | 635 |
| Q1 | 455 | 314 | 214 | 364 | 257 | 172 |
| Q2 | 388 | 234 | 149 | 320 | 208 | 134 |
| Q3 | 368 | 228 | 138 | 351 | 244 | 160 |
| Q4 | 431 | 296 | 206 | 343 | 235 | 169 |

Note:

1. See notes in table 5

Table 7: Estimates of shape parameter $k$ (homogeneous model) for positive minute-by-minute stock returns from September 3, 1989 to March 31, 1999.

| Year | Threshold ($r$) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 0.025% | 0.05% | 0.075% | 0.1% | 0.125% | 0.15% | 0.175% | 0.2% |
| 1989 | -0.1466 | -0.1960 | -0.2421 | -0.2734 | -0.2785 | -0.2815 | -0.3537 | -0.3574 |
| | (0.0136) | (0.0170) | (0.0243) | (0.0325) | (0.0436) | (0.0530) | (0.0723) | (0.0876) |
| 1990 | -0.1106 | -0.0996 | -0.0824 | -0.1678 | -0.2642 | -0.2810 | -0.3573 | -0.3944 |
| | (0.0127) | (0.0142) | (0.0163) | (0.0256) | (0.0445) | (0.0565) | (0.0806) | (0.1066) |
| 1991 | -0.1317 | -0.1285 | -0.1953 | -0.3205 | -0.4544 | -0.6067 | -0.5970 | -0.4732 |
| | (0.0128) | (0.0140) | (0.0210) | (0.0369) | (0.0624) | (0.1035) | (0.1457) | (0.1642) |
| 1992 | -0.0844 | -0.1382 | -0.1290 | -0.2021 | -0.3042 | -0.3733 | -0.5295 | -0.5273 |
| | (0.0087) | (0.0126) | (0.0135) | (0.0195) | (0.0307) | (0.0434) | (0.0685) | (0.0918) |
| 1993 | -0.0695 | -0.0694 | -0.1244 | -0.2016 | -0.2696 | -0.3437 | -0.4595 | -0.6254 |
| | (0.0075) | (0.0075) | (0.0113) | (0.0171) | (0.0244) | (0.0346) | (0.0514) | (0.0808) |
| 1994 | -0.1593 | -0.2432 | -0.2648 | -0.3110 | -0.3895 | -0.4694 | -0.5424 | -0.5893 |
| | (0.0104) | (0.0150) | (0.0184) | (0.0240) | (0.0329) | (0.0448) | (0.0611) | (0.0794) |
| 1995 | -0.1681 | -0.2584 | -0.3979 | -0.5988 | -0.7049 | -0.7308 | -0.4664 | -0.2623 |
| | (0.0111) | (0.0164) | (0.0255) | (0.0463) | (0.0744) | (0.1115) | (0.1217) | (0.1202) |
| 1996 | -0.1711 | -0.2306 | -0.4053 | -0.5482 | -0.6634 | -0.6635 | -0.6338 | -0.3877 |
| | (0.0118) | (0.0148) | (0.0273) | (0.0468) | (0.0729) | (0.1046) | (0.1367) | (0.1348) |
| 1997 | -0.2180 | -0.2473 | -0.3096 | -0.4247 | -0.4974 | -0.5642 | -0.6434 | -0.6367 |
| | (0.0116) | (0.0125) | (0.0158) | (0.0224) | (0.0302) | (0.0400) | (0.0538) | (0.0651) |
| 1998 | -0.1976 | -0.2236 | -0.2742 | -0.3412 | -0.4233 | -0.5050 | -0.5813 | -0.6098 |
| | (0.0098) | (0.0107) | (0.0132) | (0.0169) | (0.0221) | (0.0292) | (0.0380) | (0.0466) |
| 1999 | -0.2255 | -0.1963 | -0.2257 | -0.2920 | -0.4504 | -0.5321 | -0.6524 | -0.7639 |
| | (0.0247) | (0.0211) | (0.0248) | (0.0315) | (0.0474) | (0.0629) | (0.0866) | (0.1124) |

Notes:

1. Standard errors are in parentheses.

Table 8: Estimates of shape parameter $k$ (homogeneous model) for negative minute-by-minute stock returns from September 3, 1989 to March 31, 1999.

| Year | Threshold ($r$) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 0.025% | 0.05% | 0.075% | 0.1% | 0.125% | 0.15% | 0.175% | 0.2% |
| 1989 | -0.2146 | -0.2762 | -0.3591 | -0.5033 | -0.6385 | -0.6963 | -0.8127 | -0.8569 |
| | (0.0140) | (0.0171) | (0.0242) | (0.0362) | (0.0557) | (0.0746) | (0.1033) | (0.1305) |
| 1990 | -0.1358 | -0.1452 | -0.1328 | -0.2480 | -0.3850 | -0.4159 | -0.4907 | -0.4143 |
| | (0.0129) | (0.0131) | (0.0189) | (0.0288) | (0.0507) | (0.0714) | (0.1011) | (0.1333) |
| 1991 | -0.1303 | -0.1296 | -0.1861 | -0.3132 | -0.3743 | -0.4147 | -0.4107 | -0.5002 |
| | (0.0135) | (0.0154) | (0.0221) | (0.0408) | (0.0664) | (0.0924) | (0.1188) | (0.1609) |
| 1992 | -0.0787 | -0.1452 | -0.1307 | -0.2009 | -0.3040 | -0.3760 | -0.4723 | -0.5339 |
| | (0.0085) | (0.0131) | (0.0138) | (0.0200) | (0.0307) | (0.0442) | (0.0645) | (0.0934) |
| 1993 | -0.0563 | -0.0545 | -0.1095 | -0.1972 | -0.2711 | -0.3195 | -0.4687 | -0.5966 |
| | (0.0069) | (0.0069) | (0.0109) | (0.0177) | (0.0265) | (0.0362) | (0.0564) | (0.0843) |
| 1994 | -0.1711 | -0.2512 | -0.2770 | -0.3077 | -0.3845 | -0.4500 | -0.5326 | -0.5414 |
| | (0.0107) | (0.0150) | (0.0185) | (0.0232) | (0.0313) | (0.0420) | (0.0564) | (0.0698) |
| 1995 | -0.1485 | -0.2268 | -0.3814 | -0.4594 | -0.6136 | -0.6526 | -0.4712 | -0.3367 |
| | (0.0109) | (0.0160) | (0.0268) | (0.0427) | (0.0699) | (0.1038) | (0.1189) | (0.1224) |
| 1996 | -0.1502 | -0.2090 | -0.3664 | -0.5020 | -0.6524 | -0.7100 | -0.8938 | -0.6639 |
| | (0.0110) | (0.0142) | (0.0267) | (0.0456) | (0.0759) | (0.1040) | (0.1563) | (0.1730) |
| 1997 | -0.2400 | -0.2719 | -0.3321 | -0.4282 | -0.4891 | -0.5305 | -0.5472 | -0.5515 |
| | (0.0121) | (0.0131) | (0.0165) | (0.0225) | (0.0297) | (0.0379) | (0.0463) | (0.0535) |
| 1998 | -0.1819 | -0.2058 | -0.2544 | -0.3352 | -0.4188 | -0.5048 | -0.5605 | -0.6333 |
| | (0.0094) | (0.0104) | (0.0128) | (0.0169) | (0.0223) | (0.0296) | (0.0380) | (0.0492) |
| 1999 | -0.2204 | -0.1804 | -0.2153 | -0.2919 | -0.4352 | -0.5590 | -0.6290 | -0.8147 |
| | (0.0254) | (0.0211) | (0.0251) | (0.0327) | (0.0481) | (0.0682) | (0.0896) | (0.1303) |

Notes:

1. See note in table 7.

Table 9: Estimates of location parameter $\mu$ (homogeneous model) for positive minute-by-minute stock returns from September 3, 1989 to March 31, 1999.

| Year | Threshold ($r$) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 0.025% | 0.05% | 0.075% | 0.1% | 0.125% | 0.15% | 0.175% | 0.2% |
| 1989 | 0.2215 | 0.2219 | 0.2235 | 0.2218 | 0.2218 | 0.2217 | 0.2191 | 0.2193 |
| | (0.0051) | (0.0048) | (0.0049) | (0.0049) | (0.0051) | (0.00530 | (0.0051) | (0.0051) |
| 1990 | 0.1869 | 0.1864 | 0.1891 | 0.1824 | 0.1777 | 0.1782 | 0.1790 | 0.1799 |
| | (0.0034) | (0.0028) | (0.0029) | (0.0029) | (0.0031) | (0.0030) | (0.0028) | (0.0045) |
| 1991 | 0.1679 | 0.1675 | 0.1637 | 0.1581 | 0.1541 | 0.1543 | 0.1540 | 0.1399 |
| | (0.0033) | (0.0026) | (0.0027) | (0.0028) | (0.0027) | (0.0023) | (0.0050) | (0.0155) |
| 1992 | 0.2329 | 0.2341 | 0.2334 | 0.2276 | 0.2221 | 0.2186 | 0.2135 | 0.2135 |
| | (0.0035) | (0.0039) | (0.0034) | (0.0036) | (0.0038) | (0.0039) | (0.0036) | (0.0037) |
| 1993 | 0.2595 | 0.2574 | 0.2497 | 0.2444 | 0.2402 | 0.2355 | 0.2297 | 0.2257 |
| | (0.0035) | (0.0031) | (0.0035) | (0.0038) | (0.0039) | (0.0040) | (0.0039) | (0.0035) |
| 1994 | 0.2608 | 0.2665 | 0.2667 | 0.2646 | 0.2598 | 0.2547 | 0.2506 | 0.2491 |
| | (0.0049) | (0.0057) | (0.0054) | (0.0054) | (0.0056) | (0.0057) | (0.0058) | (0.0058) |
| 1995 | 0.1868 | 0.1861 | 0.1796 | 0.1722 | 0.1686 | 0.1680 | 0.1622 | 0.1394 |
| | (0.0035) | (0.0037) | (0.0039) | (0.0041) | ( 0.0042) | ( 0.0043) | (0.0069) | (0.0147) |
| 1996 | 0.1763 | 0.1734 | 0.1689 | 0.1636 | 0.1604 | 0.1594 | 0.1587 | 0.1330 |
| | (0.0035) | (0.0031) | (0.0036) | (0.0036) | (0.0036) | (0.0037) | (0.0052) | (0.0151) |
| 1997 | 0.3193 | 0.3210 | 0.3210 | 0.3195 | 0.3173 | 0.3131 | 0.3075 | 0.3080 |
| | (0.0074) | (0.0066) | (0.0069) | (0.0077) | (0.0079) | (0.0080) | (0.0082) | (0.0086) |
| 1998 | 0.3788 | 0.3809 | 0.3820 | 0.3812 | 0.3785 | 0.3745 | 0.3690 | 0.3668 |
| | (0.0076) | (0.0071) | (0.0076) | (0.0081) | (0.0087) | (0.0091) | (0.0093) | (0.0095) |
| 1999 | 0.3530 | 0.3483 | 0.3469 | 0.3387 | 0.3264 | 0.3212 | 0.3120 | 0.3032 |
| | (0.0173) | (0.0121) | (0.0123) | (0.0130) | (0.0149) | (0.0152) | (0.0154) | (0.0150) |

Notes:

1. See note in table 7.

Table 10: Estimates of location parameter $\mu$ (homogeneous model) for negative minute-by-minute stock returns from September 3, 1989 to March 31, 1999.

| Year | Threshold ($r$) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 0.025% | 0.05% | 0.075% | 0.1% | 0.125% | 0.15% | 0.175% | 0.2% |
| 1989 | 0.2420 | 0.2420 | 0.2422 | 0.2339 | 0.2270 | 0.2240 | 0.2193 | 0.2192 |
| | (0.0065) | (0.0061) | (0.0065) | (0.0068) | (0.0070) | (0.0071) | (0.0068) | (0.0065) |
| 1990 | 0.1921 | 0.2321 | 0.1936 | 0.1859 | 0.1798 | 0.1794 | 0.1808 | 0.1770 |
| | (0.0037) | (0.0039) | (0.0032) | (0.0033) | (0.0034) | (0.0035) | (0.0032) | (0.0060) |
| 1991 | 0.1631 | 0.1621 | 0.1591 | 0.1542 | 0.1522 | 0.1536 | 0.1543 | 0.1646 |
| | (0.0032) | (0.0026) | (0.0026) | (0.0028) | (0.0029) | (0.0028) | (0.0048) | (0.0087) |
| 1992 | 0.2308 | 0.2321 | 0.2310 | 0.2261 | 0.2200 | 0.2164 | 0.2132 | 0.2117 |
| | (0.0033) | (0.0039) | (0.0034) | (0.0036) | (0.0037) | (0.0038) | (0.0037) | (0.0036) |
| 1993 | 0.2475 | 0.2458 | 0.2358 | 0.2294 | 0.2255 | 0.2227 | 0.2168 | 0.2156 |
| | (0.0031) | (0.0028) | (0.0031) | (0.0034) | (0.0036) | (0.0037) | (0.0034) | (0.0030) |
| 1994 | 0.2737 | 0.2800 | 0.2802 | 0.2787 | 0.2737 | 0.2693 | 0.2641 | 0.2637 |
| | (0.0054) | (0.0062) | (0.0058) | (0.0058) | (0.0060) | (0.0061) | (0.0061) | (0.0063) |
| 1995 | 0.1795 | 0.1792 | 0.1732 | 0.1707 | 0.1653 | 0.1649 | 0.1594 | 0.1446 |
| | (0.0032) | (0.0034) | (0.0037) | (0.0038) | (0.0037) | (0.0037) | (0.0059) | (0.0124) |
| 1996 | 0.1681 | 0.1645 | 0.1597 | 0.1545 | 0.1508 | 0.1518 | 0.1590 | 0.1337 |
| | (0.0031) | (0.0028) | (0.0031) | (0.0032) | (0.0030) | (0.0028) | (0.0038) | (0.0165) |
| 1997 | 0.3428 | 0.3457 | 0.3479 | 0.3483 | 0.3474 | 0.3448 | 0.3435 | 0.3430 |
| | ( 0.0085) | (0.0076) | (0.0079) | (0.0087) | (0.0089) | (0.0090) | (0.0092) | (0.0094) |
| 1998 | 0.3753 | 0.3767 | 0.3777 | 0.3773 | 0.3760 | 0.3722 | 0.3685 | 0.3625 |
| | (0.0071) | (0.0067) | (0.0071) | (0.0080) | (0.0086) | (0.0090) | (0.0091) | (0.0093) |
| 1999 | 0.3455 | 0.3399 | 0.3367 | 0.3286 | 0.3196 | 0.3126 | 0.3075 | 0.2954 |
| | (0.0170) | (0.0115) | (0.0117) | (0.0126) | (0.0142) | (0.0149) | (0.0149) | (0.0147) |

Notes:

1. See note in table 7.

Table 11: Estimates of scale parameter $\sigma$ (homogeneous model) for positive minute-by-minute stock returns from September 3, 1989 to March 31, 1999.

| Year | Threshold ($r$) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 0.025% | 0.05% | 0.075% | 0.1% | 0.125% | 0.15% | 0.175% | 0.2% |
| 1989 | 0.0647 | 0.0693 | 0.0745 | 0.0750 | 0.0762 | 0.0756 | 0.0709 | 0.0705 |
| | (0.0032) | (0.0035) | (0.0041) | (0.0043) | (0.0044) | (0.0046) | (0.0053) | (0.0069) |
| 1990 | 0.0525 | 0.0514 | 0.0528 | 0.0507 | 0.0505 | 0.0484 | 0.0429 | 0.0402 |
| | (0.0022) | (0.0019) | (0.0018) | (0.0021) | (0.0026) | (0.0031) | (0.0043) | (0.0067) |
| 1991 | 0.0477 | 0.0473 | 0.0480 | 0.0478 | 0.0436 | 0.0358 | 0.0364 | 0.0485 |
| | (0.0021) | (0.0017) | (0.0020) | (0.0025) | (0.0029) | (0.0041) | (0.0080) | (0.0155) |
| 1992 | 0.0593 | 0.0649 | 0.0636 | 0.0649 | 0.0668 | 0.0651 | 0.0578 | 0.0580 |
| | (0.0019) | (0.0025) | (0.0022) | (0.0028) | (0.0034) | (0.0036) | (0.0041) | (0.0057) |
| 1993 | 0.0638 | 0.0628 | 0.0643 | 0.0674 | 0.0689 | 0.0681 | 0.0635 | 0.0542 |
| | (0.0018) | (0.0016) | (0.0021) | (0.0028) | (0.0033) | (0.0036) | (0.0040) | (0.0045) |
| 1994 | 0.0789 | 0.0917 | 0.0943 | 0.0971 | 0.0990 | 0.0980 | 0.0952 | 0.0915 |
| | (0.0030) | (0.0043) | (0.0044) | (0.0048) | (0.0055) | (0.0059) | (0.0063) | (0.0071) |
| 1995 | 0.0580 | 0.0646 | 0.0688 | 0.0714 | 0.0684 | 0.0672 | 0.0948 | 0.1351 |
| | (0.0022) | (0.0029) | (0.0038) | (0.0048) | (0.0052) | (0.0073) | (0.0144) | (0.0249) |
| 1996 | 0.0538 | 0.0561 | 0.0638 | 0.0640 | 0.0591 | 0.0600 | 0.0625 | 0.0987 |
| | (0.0023) | (0.0023) | (0.0035) | (0.0040) | (0.0044) | (0.0067) | (0.0111) | (0.0220) |
| 1997 | 0.1070 | 0.1122 | 0.1211 | 0.1356 | 0.1426 | 0.1451 | 0.1449 | 0.1450 |
| | (0.0048) | (0.0047) | (0.0055) | (0.0075) | (0.0085) | (0.0092) | (0.0099) | (0.0100) |
| 1998 | 0.1220 | 0.1277 | 0.1372 | 0.1479 | 0.1586 | 0.1669 | 0.1708 | 0.1715 |
| | (0.0047) | (0.0048) | (0.0057) | (0.0069) | (0.0084) | (0.0098) | (0.0108) | (0.0111) |
| 1999 | 0.1207 | 0.1134 | 0.1173 | 0.1213 | 0.1321 | 0.1363 | 0.1367 | 0.1307 |
| | (0.0114) | (0.0080) | (0.0087) | (0.0103) | (0.0147) | (0.0165) | (0.0186) | (0.0196) |

Notes:

1. See note in table 7.

Table 12: Estimates of scale parameter $\sigma$ (homogeneous model) for negative minute-by-minute stock returns from September 3, 1989 to March 31, 1999.

| Year | Threshold ($r$) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 0.025% | 0.05% | 0.075% | 0.1% | 0.125% | 0.15% | 0.175% | 0.2% |
| 1989 | 0.0810 | 0.0878 | 0.0967 | 0.1016 | 0.1035 | 0.1008 | 0.0924 | 0.0877 |
| | (0.0042) | (0.0047) | (0.0058) | (0.0073) | (0.0084) | (0.0087) | (0.0096) | (0.0118) |
| 1990 | 0.0569 | 0.0651 | 0.0582 | 0.0570 | 0.0565 | 0.0546 | 0.0489 | 0.0558 |
| | (0.0024) | (0.0026) | (0.0022) | (0.0027) | (0.0033) | (0.0039) | (0.0055) | (0.0108) |
| 1991 | 0.0464 | 0.0457 | 0.0460 | 0.0468 | 0.0457 | 0.0424 | 0.0424 | 0.0339 |
| | (0.0021) | (0.0018) | (0.0020) | (0.0025) | (0.0031) | (0.0046) | (0.0077) | (0.0099) |
| 1992 | 0.0584 | 0.0651 | 0.0632 | 0.0649 | 0.0654 | 0.0639 | 0.0594 | 0.0562 |
| | (0.0018) | (0.0026) | (0.0023) | (0.0028) | (0.0033) | (0.0036) | (0.0041) | (0.0057) |
| 1993 | 0.0596 | 0.0585 | 0.0586 | 0.0612 | 0.0626 | 0.0617 | 0.0542 | 0.0465 |
| | (0.0016) | (0.0014) | (0.0019) | (0.0026) | (0.0030) | (0.0032) | (0.0035) | (0.0043) |
| 1994 | 0.0849 | 0.0982 | 0.1014 | 0.1034 | 0.1057 | 0.1057 | 0.1022 | 0.1016 |
| | (0.0033) | (0.0046) | (0.0048) | (0.0051) | (0.0058) | (0.0062) | (0.0066) | (0.0072) |
| 1995 | 0.0538 | 0.0593 | 0.0643 | 0.0657 | 0.0606 | 0.0583 | 0.0756 | 0.0975 |
| | (0.0020) | (0.0026) | (0.0035) | (0.0039) | (0.0044) | (0.0061) | (0.0117) | (0.0192) |
| 1996 | 0.0493 | 0.0509 | 0.0564 | 0.0555 | 0.0494 | 0.0452 | 0.0327 | 0.0540 |
| | (0.0019) | (0.0020) | (0.0029) | (0.0034) | (0.0039) | (0.0054) | (0.0070) | (0.0169) |
| 1997 | 0.1206 | 0.1274 | 0.1384 | 0.1534 | 0.1614 | 0.1638 | 0.1640 | 0.1632 |
| | (0.0057) | (0.0056) | (0.0066) | (0.0084) | (0.0096) | (0.0101) | (0.0103) | (0.0103) |
| 1998 | 0.1172 | 0.1221 | 0.1310 | 0.1439 | 0.1558 | 0.1646 | 0.1675 | 0.1676 |
| | (0.0043) | (0.0044) | (0.0052) | (0.0067) | (0.0083) | (0.0097) | (0.0105) | (0.0112) |
| 1999 | 0.1172 | 0.1080 | 0.1112 | 0.1162 | 0.1267 | 0.1329 | 0.1327 | 0.1259 |
| | (0.0113) | (0.0075) | (0.0083) | (0.0101) | (0.0140) | (0.0169) | (0.0178) | (0.0197) |

Notes:

1. See note in table 7.

Table 13: Estimates of conditional scale parameter $\psi$ (homogeneous model) for positive minute-by-minute stock returns from September 3, 1989 to March 31, 1999.

| Year | Threshold ($r$) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 0.025% | 0.05% | 0.075% | 0.1% | 0.125% | 0.15% | 0.175% | 0.2% |
| 1989 | 0.0359 | 0.0356 | 0.0385 | 0.0417 | 0.0492 | 0.0554 | 0.0553 | 0.0636 |
| 1990 | 0.0346 | 0.0378 | 0.0434 | 0.0369 | 0.0366 | 0.0405 | 0.0415 | 0.0481 |
| 1991 | 0.0289 | 0.0322 | 0.0307 | 0.0292 | 0.0304 | 0.0332 | 0.0489 | 0.0769 |
| 1992 | 0.0418 | 0.0395 | 0.0432 | 0.0391 | 0.0373 | 0.0395 | 0.0374 | 0.0509 |
| 1993 | 0.0475 | 0.0484 | 0.0426 | 0.0383 | 0.0378 | 0.0387 | 0.0384 | 0.0381 |
| 1994 | 0.0413 | 0.0390 | 0.0435 | 0.0459 | 0.0465 | 0.0489 | 0.0542 | 0.0626 |
| 1995 | 0.0308 | 0.0294 | 0.0272 | 0.0282 | 0.0377 | 0.0540 | 0.1008 | 0.1510 |
| 1996 | 0.0279 | 0.0276 | 0.0257 | 0.0291 | 0.0356 | 0.0538 | 0.0728 | 0.1247 |
| 1997 | 0.0428 | 0.0452 | 0.0449 | 0.0424 | 0.0469 | 0.0531 | 0.0596 | 0.0762 |
| 1998 | 0.0521 | 0.0537 | 0.0530 | 0.0520 | 0.0513 | 0.0535 | 0.0580 | 0.0698 |
| 1999 | 0.0467 | 0.0548 | 0.0559 | 0.0516 | 0.0414 | 0.0452 | 0.0473 | 0.0519 |

Notes:

1. See note in table 7.

Table 14: Estimates of conditional scale parameter $\psi$ (homogeneous model) for negative minute-by-minute stock returns from September 3, 1989 to March 31, 1999.

| Year | Threshold ($r$) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 0.025% | 0.05% | 0.075% | 0.1% | 0.125% | 0.15% | 0.175% | 0.2% |
| 1989 | 0.0344 | 0.0348 | 0.0367 | 0.0342 | 0.0384 | 0.0493 | 0.0564 | 0.0712 |
| 1990 | 0.0342 | 0.0387 | 0.0424 | 0.0357 | 0.0354 | 0.0424 | 0.0461 | 0.0653 |
| 1991 | 0.0284 | 0.0312 | 0.0303 | 0.0298 | 0.0355 | 0.0409 | 0.0509 | 0.0516 |
| 1992 | 0.0422 | 0.0387 | 0.0428 | 0.0396 | 0.0365 | 0.0389 | 0.0414 | 0.0500 |
| 1993 | 0.0471 | 0.0478 | 0.0410 | 0.0357 | 0.0354 | 0.0385 | 0.0346 | 0.0372 |
| 1994 | 0.0423 | 0.0404 | 0.0446 | 0.0484 | 0.0485 | 0.0520 | 0.0547 | 0.0671 |
| 1995 | 0.0309 | 0.0300 | 0.0268 | 0.0332 | 0.0359 | 0.0486 | 0.0830 | 0.1162 |
| 1996 | 0.0278 | 0.0270 | 0.0254 | 0.0281 | 0.0326 | 0.0439 | 0.0470 | 0.0980 |
| 1997 | 0.0443 | 0.0470 | 0.0478 | 0.0471 | 0.0526 | 0.0605 | 0.0718 | 0.0843 |
| 1998 | 0.0535 | 0.0549 | 0.0540 | 0.0509 | 0.0507 | 0.0524 | 0.0590 | 0.0647 |
| 1999 | 0.0466 | 0.0557 | 0.0549 | 0.0495 | 0.0420 | 0.0420 | 0.0494 | 0.0482 |

Notes:

1. See note in table 7.

Table 15: Estimates of shape parameter $k$, location parameter $\mu$ and scale parameter $\sigma$ the daily stock returns from December 8, 1972 to March 3, 2000 using the homogeneous model.

| | Positive Returns | | | | |
|---|---|---|---|---|---|
| $r$ | times | $k$ | $\mu$ | $\sigma$ | $\psi$ |
| 1% | 1642 | -0.1838<br>(0.0282) | 3.0377<br>(0.0688) | 1.4498<br>(0.0533) | 1.0753 |
| 1.5% | 1072 | -0.2275<br>(0.0375) | 2.9919<br>(0.0708) | 1.4210<br>(0.0571) | 1.0816 |
| 2% | 707 | -0.2767<br>(0.0510) | 2.9610<br>(0.0712) | 1.3645<br>(0.0657) | 1.0986 |
| | Negative Returns | | | | |
| 1% | 1378 | -0.1573<br>(0.0298) | 2.9877<br>(0.0742) | 1.5324<br>(0.0551) | 1.2197 |
| 1.5% | 944 | -0.1887<br>(0.0384) | 2.9560<br>(0.0757) | 1.4996<br>(0.0596) | 1.2249 |
| 2% | 635 | -0.1822<br>(0.0456) | 2.9601<br>(0.0777) | 1.5096<br>(0.0717) | 1.3347 |

Note:

1. The numbers in parentheses are standard errors.
2. $\psi$ is obtained by $\psi = \sigma - k(r - \mu)$

Table 16: Estimates of the inhomogeneous model allowing time-vary shape parameter ($k_t$), location parameter ($\mu_t$) and scale parameter ($\sigma_t$) over 1% threshold ($r$) of daily stock returns from December 8, 1972 to March 3, 2000.

| | Positive Returns | | | Negative Returns | | |
|---|---|---|---|---|---|---|
| Variable | $k_t$ | $\ln(\sigma_t)$ | $\mu_t$ | $k_t$ | $\ln(\sigma_t)$ | $\mu_t$ |
| (1) constant | 0.1807* (0.0435) | -0.6506* (0.0771) | 1.7391* (0.1284) | 0.0686 (0.0578) | -0.4536* (0.0915) | 1.3508* (0.1311) |
| (2) $x_{1t}$ | 0.0354* (0.0137) | 0.0595* (0.0222) | 0.5422* (0.0459) | | 0.0384* (0.0078) | |
| (3) $x_{2t}$ | -0.0374* (0.0082) | 0.1592* (0.0118) | 0.2406* (0.0213) | -0.0002 (0.0098) | 0.1109* (0.0146) | 0.2773* (0.0279) |
| (4) $x_{3t}$ | 0.0019 (0.0011) | 0.0047* (0.0011) | 0.0243* (0.0076) | -0.0024* (0.0012) | 0.0116* (0.0021) | 0.0254* (0.0096) |
| (5) $x_{4t}$ | 0.0037* (0.0012) | 0.0029 (0.0015) | 0.0345* (0.0080) | 0.0018 (0.0013) | 0.0025 (0.0016) | 0.0253* (0.0089) |
| (6) $x_{5t}$ | 0.0048* (0.0013) | 0.0018 (0.0015) | 0.0350* (0.0062) | 0.0060* (0.0026) | 0.0012 (0.0025) | 0.04778* (0.0082) |
| (7) $x_{6t}$ | | | | -0.1076* (0.0360) | 0.3918* (0.0649) | 0.8689* (0.1606) |
| (8) $x_{7t}$ | | -0.0074* (0.0023) | -0.0211* (0.0057) | | 0.0032 (0.0017) | |
| (9) $x_{8t}$ | | 0.0130* (0.0039) | | | -0.0007 (0.0033) | -0.0209* (0.0051) |
| (10) $x_{9t}$ | | -0.1588* (0.0729) | 1.4020* (0.2274) | | -0.7100* (0.0344) | |

Notes:

1. $r$ is threshold; $x_{1t}$ is Dow Jones Industrial Average Returns at the $(t-1)$-th trading day; $x_{2t}$ is number of days during the previous 10 trading days with the absolute return exceeding the threshold; $x_{3t}$ $x_{4t}$ and $x_{5t}$ are, respectively, lagged 1-, lagged 2- and lagged 3-period of squared returns; $x_{6t}$ is a Monday dummy; $x_{7t}$ is a time trend; $x_{8t}$ is a duration dummy; and $x_{9t}$ is a indicator for the behavior of the previous trading day. See section 5.3 for a detailed description.

2. The numbers in parentheses are standard errors.

3. *Significant effect at the 5% level

Table 17: Estimates of the inhomogeneous model allowing time-vary shape parameter ($k_t$), location parameter ($\mu_t$) and scale parameter ($\sigma_t$) over 1.5% threshold ($r$) of daily stock returns from December 8, 1972 to March 3, 2000.

| | Positive Returns | | | Negative Returns | | |
|---|---|---|---|---|---|---|
| Variable | $k_t$ | $\ln(\sigma_t)$ | $\mu_t$ | $k_t$ | $\ln(\sigma_t)$ | $\mu_t$ |
| (1) constant | 0.0682 | -0.3141* | 1.7988* | 0.1109 | -0.3459* | 1.7311* |
| | (0.0502) | (0.0792) | (0.1212) | (0.0667) | (0.0906) | (0.1262) |
| (2) $x_{1t}$ | 0.0558* | 0.0244 | 0.5452* | -0.0436* | -0.0594* | -0.7326* |
| | (0.0166) | (0.0247) | (0.0503) | (0.0118) | (0.0144) | (0.0628) |
| (3) $x_{2t}$ | -0.0450* | 0.1619* | 0.3137* | -0.0003 | 0.0907* | 0.2801* |
| | (0.0095) | (0.0129) | (0.0269) | (0.0097) | (0.0142) | (0.0353) |
| (4) $x_{3t}$ | 0.0003 | 0.0044* | 0.0186* | -0.0017 | 0.0071* | 0.0184* |
| | (0.0012) | (0.0013) | (0.0087) | (0.0017) | (0.0019) | (0.0084) |
| (5) $x_{4t}$ | 0.1073 | -0.2236 | | 0.0057* | 0.0296* | |
| | (0.0624) | (0.1329) | | (0.0017) | (0.0087) | |
| (6) $x_{5t}$ | | | | | 0.0015 | 0.0106 |
| | | | | | (0.0012) | (0.0061) |
| (7) $x_{6t}$ | | | | -0.1082* | 0.1170 | |
| | | | | (0.0409) | (0.0601) | |
| (8) $x_{7t}$ | 0.0056* | -0.0130* | -0.0158* | -0.0045 | 0.0064 | |
| | (0.0021) | (0.0032) | (0.0059) | (0.0029) | (0.0038) | |
| (9) $x_{8t}$ | | | | | | -0.0179* |
| | | | | | | (0.0040) |
| (10) $x_{9t}$ | 0.0051** | 0.0008 | 0.0340* | | -0.1613 | 1.8836* |
| | (0.0023) | (0.0018) | (0.0064) | | (0.0974) | (0.3419) |

Note:

1. See notes in table 16

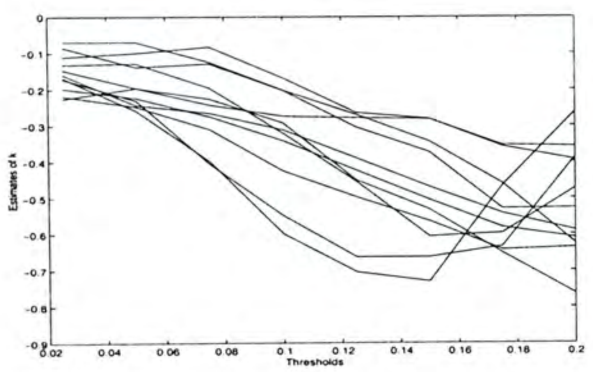
Table 18: Estimates of the inhomogeneous model allowing time-vary shape parameter ($k_t$), location parameter ($\mu_t$) and scale parameter ($\sigma_t$) over 2% threshold ($r$) of daily stock returns from December 8, 1972 to March 3, 2000.

| | Positive Returns | | | Negative Returns | | |
|---|---|---|---|---|---|---|
| Variable | $k_t$ | $\ln(\sigma_t)$ | $\mu_t$ | $k_t$ | $\ln(\sigma_t)$ | $\mu_t$ |
| (1) constant | -0.0121 | -0.1430 | 1.9400* | 0.0280 | -0.1826* | 1.7567* |
| | (0.0538) | (0.0859) | (0.1291) | (0.0469) | (0.0783) | (0.1407) |
| (2) $x_{1t}$ | 0.0327 | 0.0482 | 0.5510* | | -0.0732* | -0.6556* |
| | (0.0201) | (0.0283) | (0.0598) | | (0.0177) | (0.0649) |
| (3) $x_{2t}$ | -0.0357* | 0.1706* | 0.4518* | -0.0099 | 0.0919* | 0.3359* |
| | (0.0116) | (0.0152) | (0.0365) | (0.0107) | (0.0161) | (0.0460) |
| (4) $x_{3t}$ | 0.0002 | 0.0016 | 0.0069 | | 0.0048* | 0.0156* |
| | 0.0009 | (0.0008) | (0.0046) | | (0.0018) | (0.0083) |
| (5) $x_{4t}$ | | | 0.0015 | | 0.0053* | 0.0330* |
| | | | (0.0017) | | (0.0016) | (0.0094) |
| (6) $x_{5t}$ | | | | | 0.0013 | 0.0156 |
| | | | | | (0.0011) | (0.0083) |
| (7) $x_{6t}$ | | | | | 0.2536* | 1.1560* |
| | | | | | (0.0609) | (0.1774) |
| (8) $x_{7t}$ | 0.0075* | -0.0139* | -0.0134* | | 0.0040 | |
| | (0.0023) | (0.0032) | (0.0064) | | (0.0026) | |
| (9) $x_{8t}$ | | -0.0012 | | -0.0012 | | -0.0149* |
| | | (0.0017) | | (0.0009) | | (0.0038) |
| (10) $x_{9t}$ | 0.1084 | | 3.3344* | | | 2.7873* |
| | (0.0638) | | (0.4402) | | | (0.2578) |

Note:

1. See notes in table 16

Figure 1: Variation of shape parameter $k$ for the years investigated across thresholds

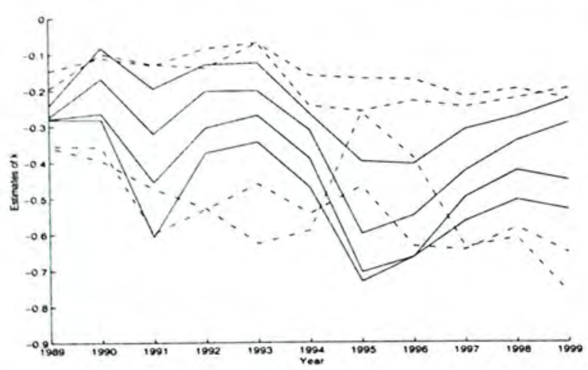


(a) positive (b) negative

Notes:

1. Figures (a) and (b) plot the rows of tables 7 and 8 respectively. Each line connects the $k$ estimates over different thresholds of a given year. Refer to tables 7 and 8 for the numbers.

Figure 2: Variation of shape parameter $k$ for all the thresholds over time

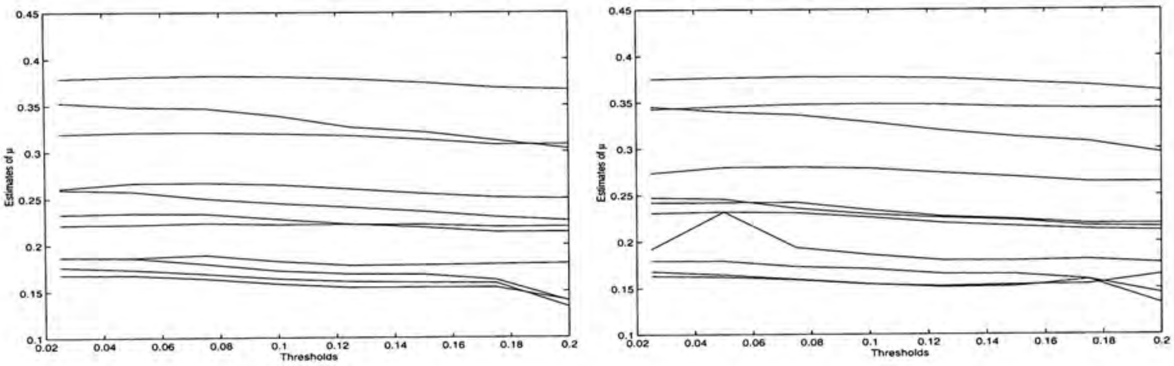


(a) positive (b) negative

Notes:

1. The dash lines, solid lines and dashdot lines are the lines connecting the estimates $k$ for $r$=0.025% to 0.05%, $r$=0.075% to 0.15% and $r$=0.175% to 0.200% respectively. Each line represents the points reported in a column of tables 7 and 8.

Figure 3: Variation of location parameter $\mu$ for the years investigated across thresholds

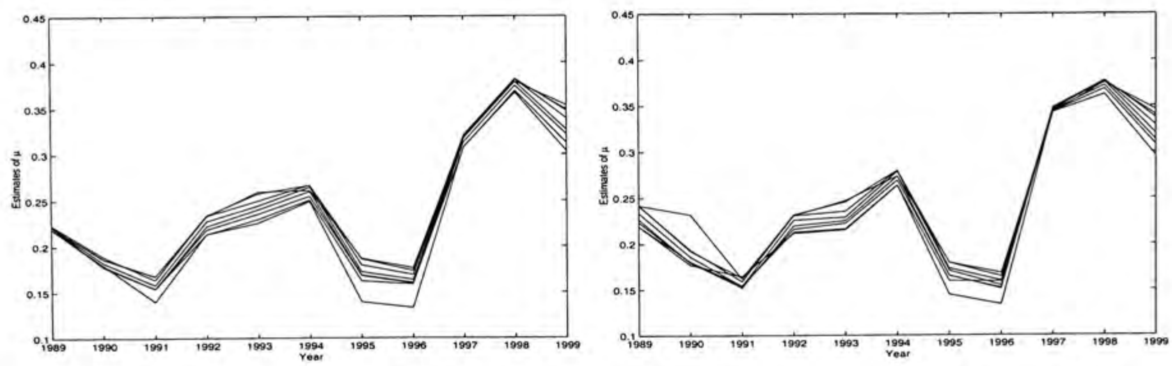



(a) positive (b) negative

Notes:

1. Figures (a) and (b) plot the rows of tables 9 and 10 respectively. Each line connects the $\mu$ estimates over different thresholds of a given year. Refer to tables 9 and 10 for the numbers.

Figure 4: Variation of location $\mu$ for all the thresholds considered over time

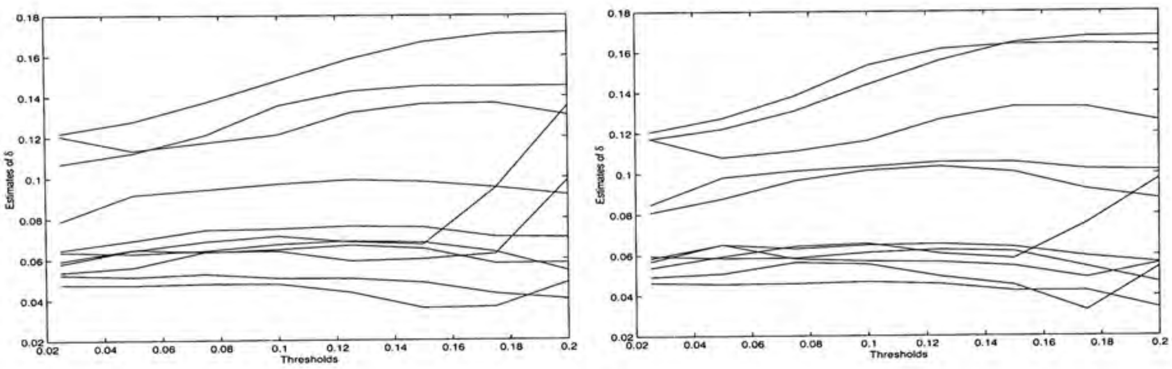



(a) positive (b) negative

Notes:

1. Each line represents the points reported in a column of tables 9 and 10.

Figure 5: Variation of scale parameter $\sigma$ for the years investigated across thresholds

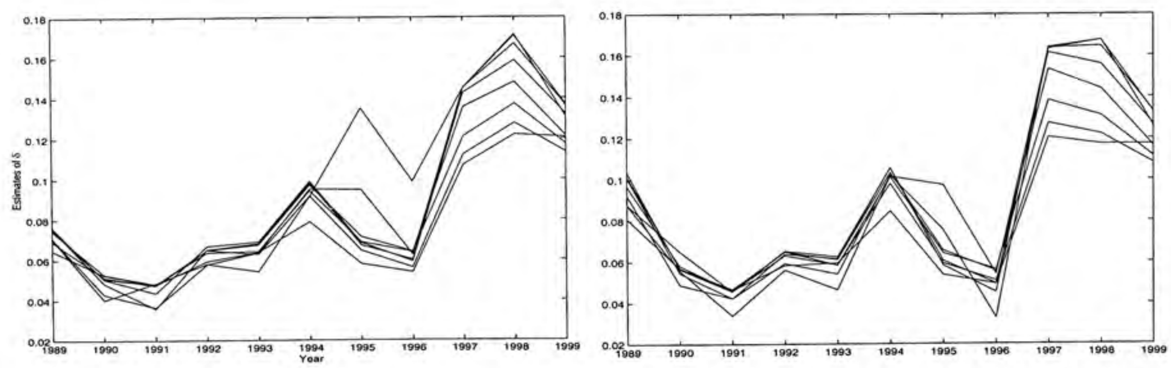



(a) positive (b) negative

Notes:

1. Figures (a) and (b) plot the rows of tables 11 and 12 respectively. Each line connects the $\delta$ estimates over different thresholds of a given year. Refer to tables 11 and 12 for the numbers.

Figure 6: Variation of scale parameter $\sigma$ for all the thresholds over time

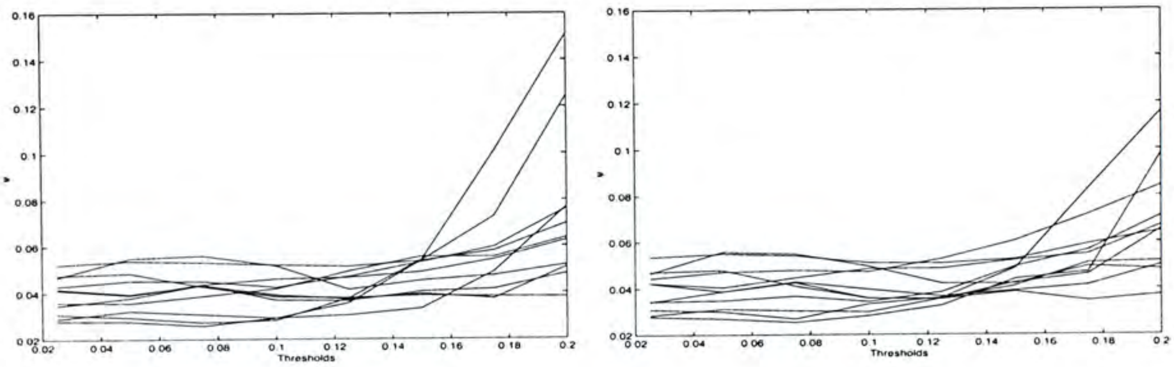



(a) positive (b) negative

Notes:

1. Each line represents the points reported in a column of tables 11 and 12.

Figure 7: Variation of conditional scale parameter $\psi$'s for the years investigated across thresholds

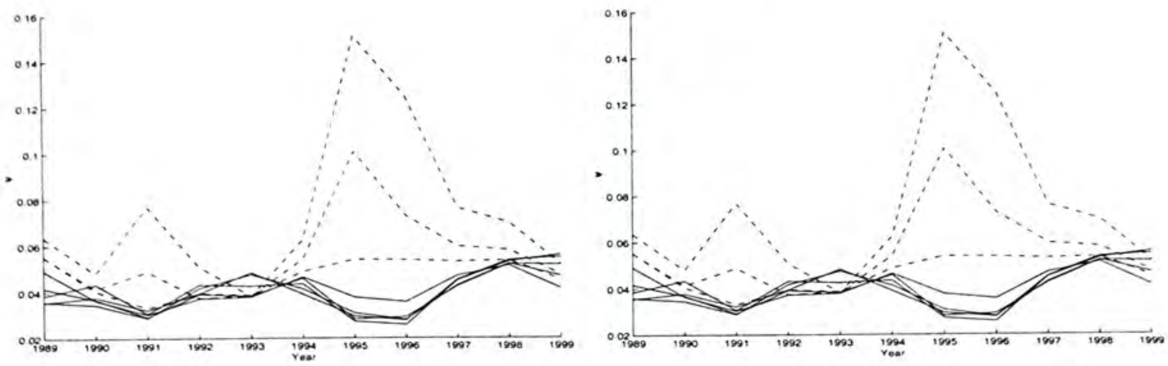



(a) positive (b) negative

Notes:

1. Figures (a) and (b) plot the rows of tables 13 and 14 respectively. Each line connects the $\psi$ estimates over different thresholds of a given year. Refer to tables 13 and 14 for the numbers.

Figure 8: Variation of conditional scale parameter $\psi$'s for all the thresholds considered over time

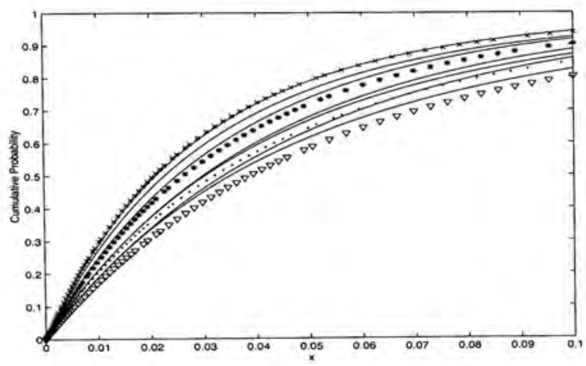



(a) positive (b) negative

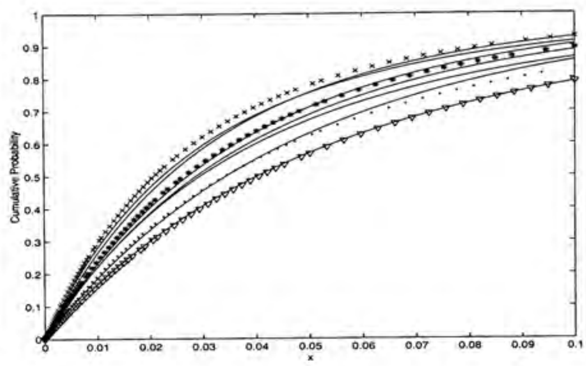
Notes:

1. The dash lines and solid lines are the lines connecting the estimates of $k$ for $r$=0.025% to 0.125% and $r$=0.15% to 0.200% respectively. Each line represents the points reported in a column of tables 13 and 14.

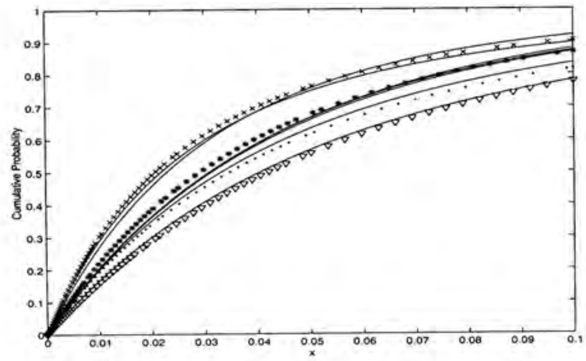
Figure 9: Plot of conditional distribution functions of excesses for positive returns



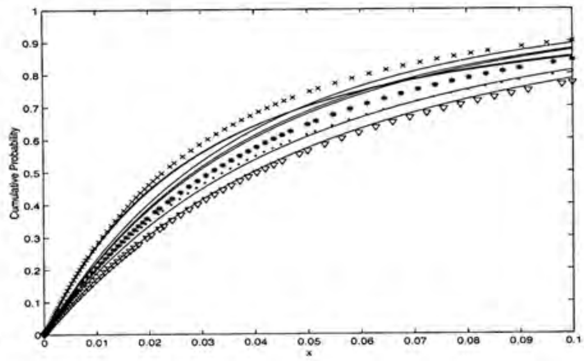

(a) $r$=0.025%



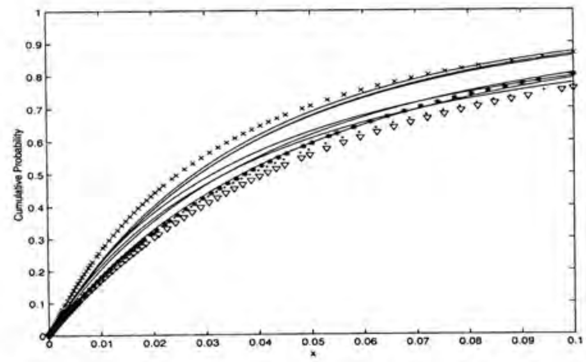

(b) $r$=0.050%



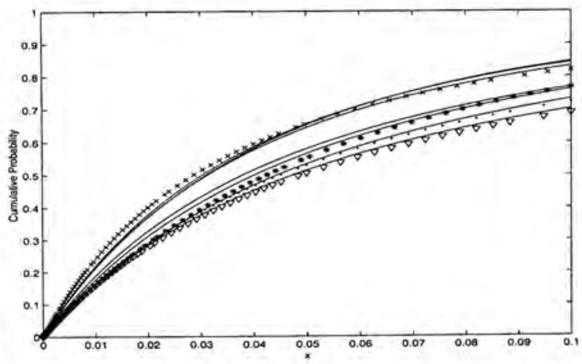

(c) $r$=0.075%



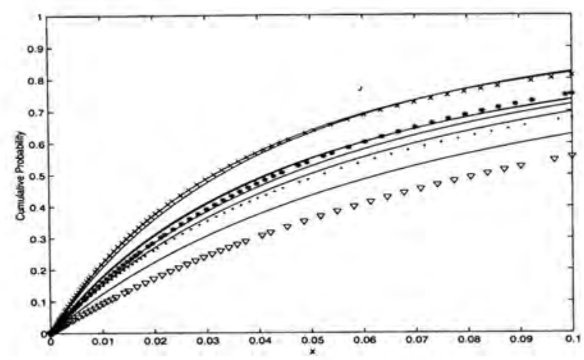

(d) $r$=0.100%



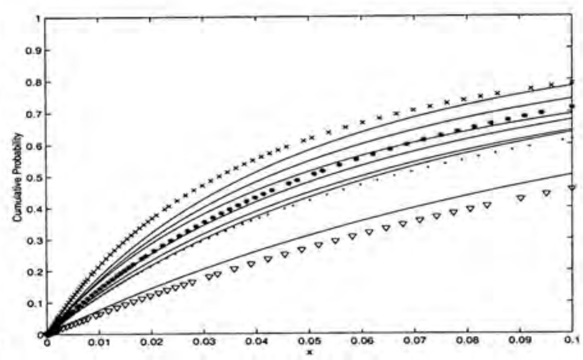

(e) $r$=0.125%




(f) $r$=0.150%




(g) $r$=0.175%



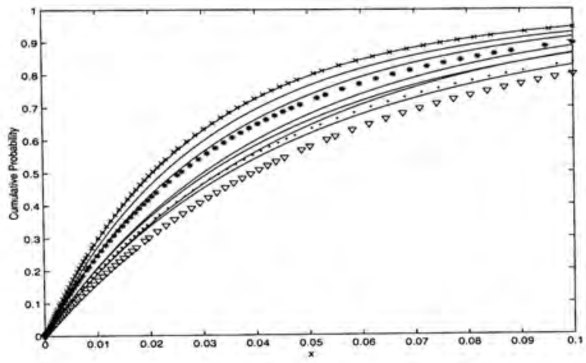

(h) $r$=0.200%



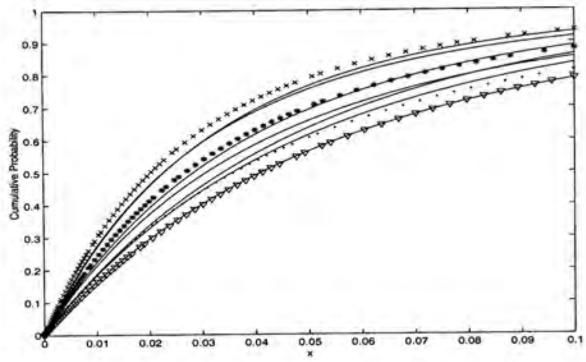
Notes:

1. The star line and dotted line are the conditional distribution functions of 1989 and 1997

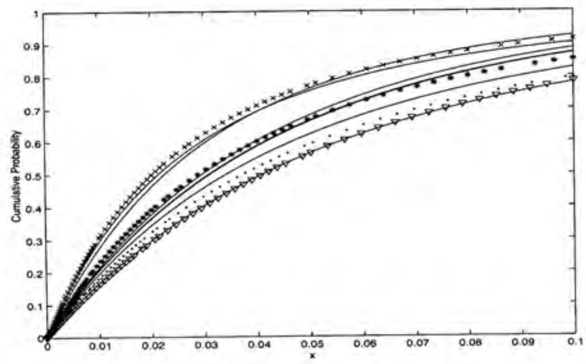
Figure 10: Plot of conditional distribution functions of excesses for negative returns



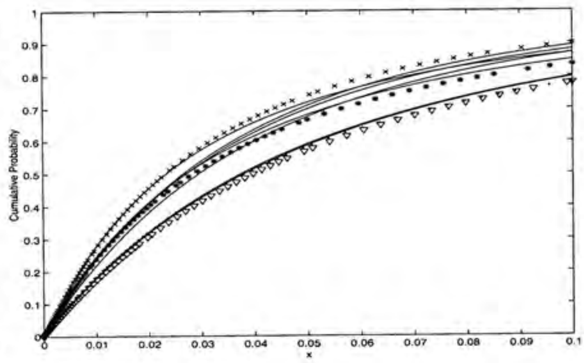

(a) $r$=0.025%



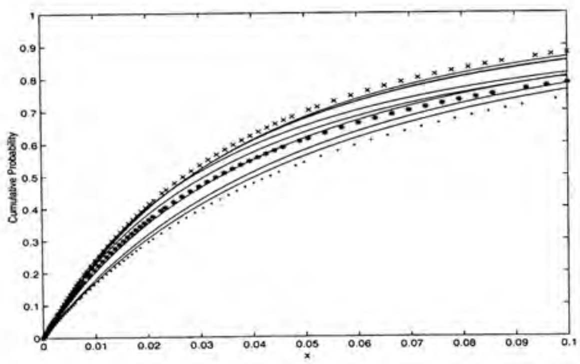

(b) $r$=0.050%



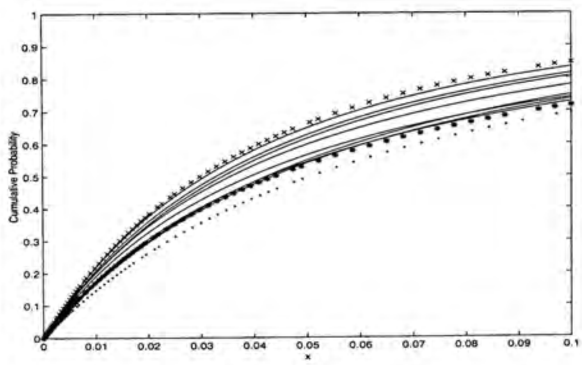

(c) $r$=0.075%



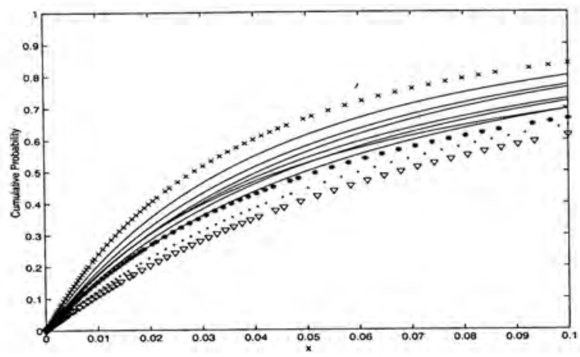

(d) $r$=0.100%



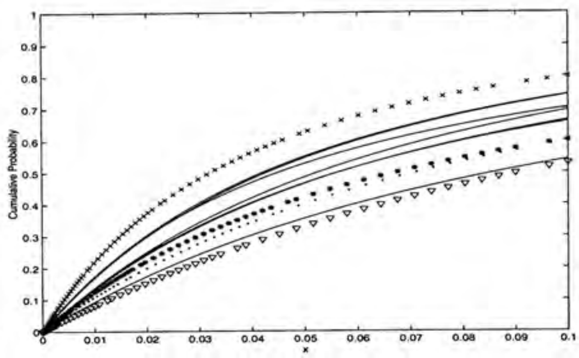

(e) $r$=0.125%




(f) $r$=0.150%




(g) $r$=0.175%



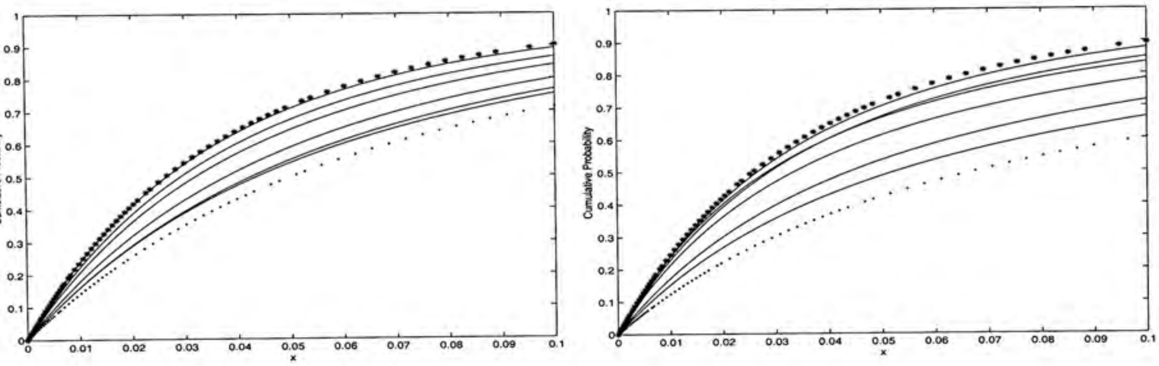

(h) $r$=0.200%



Notes:

1. The star line and dotted line are the conditional distribution functions of 1989 and 1997

Figure 11: Plot of conditional distribution functions of excesses for positive and negative returns in 1989

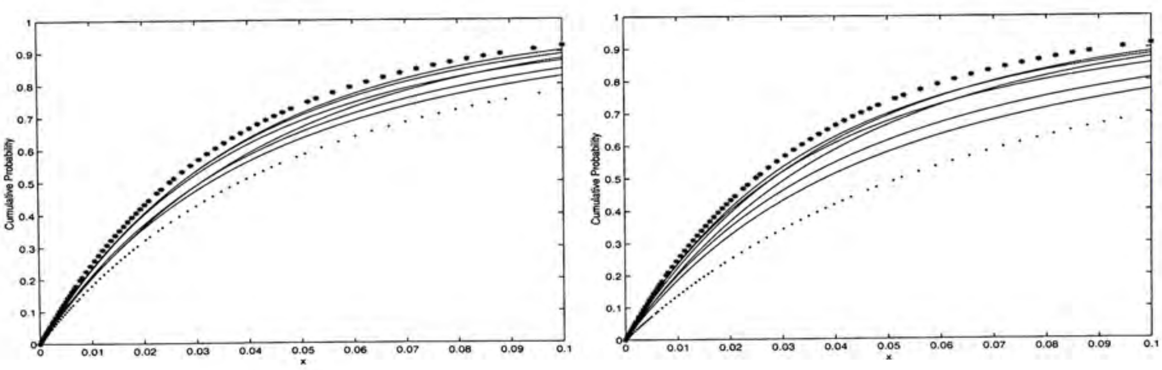



(a) positive (b) negative

Notes:

1. The star line and dotted line are the conditional distribution functions of $r$=0.025% and $r$=0.200% respectively.

Figure 12: Plot of conditional distribution functions of excesses for positive and negative returns in 1990

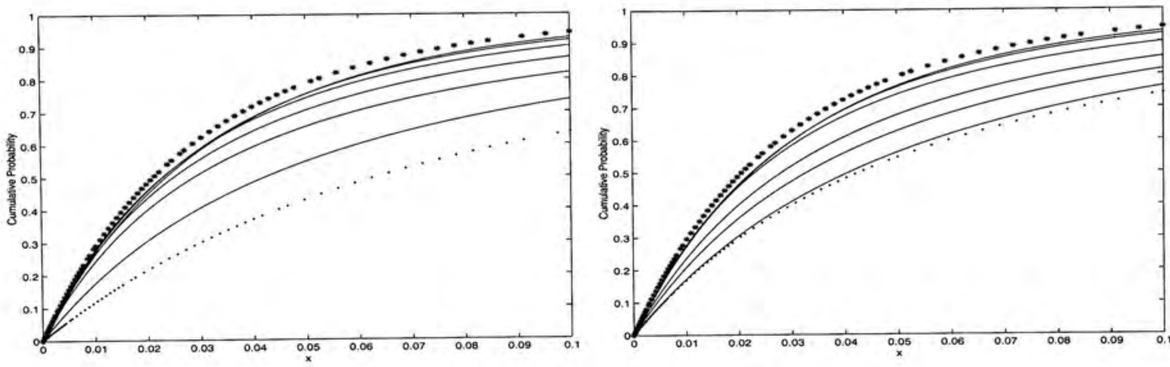



(a) positivé (b) negative

Notes:

1. See notes in figure 11.

Figure 13: Plot of conditional distribution functions of excesses for positive and negative returns in 1991

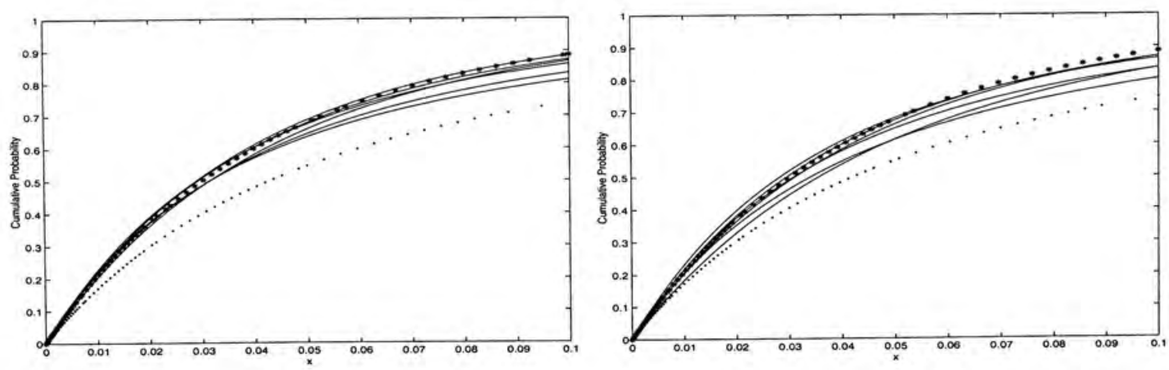



(a) positive (b) negative

Notes:

1. See notes in figure 11.

Figure 14: Plot of conditional distribution functions of excesses for positive and negative returns in 1992

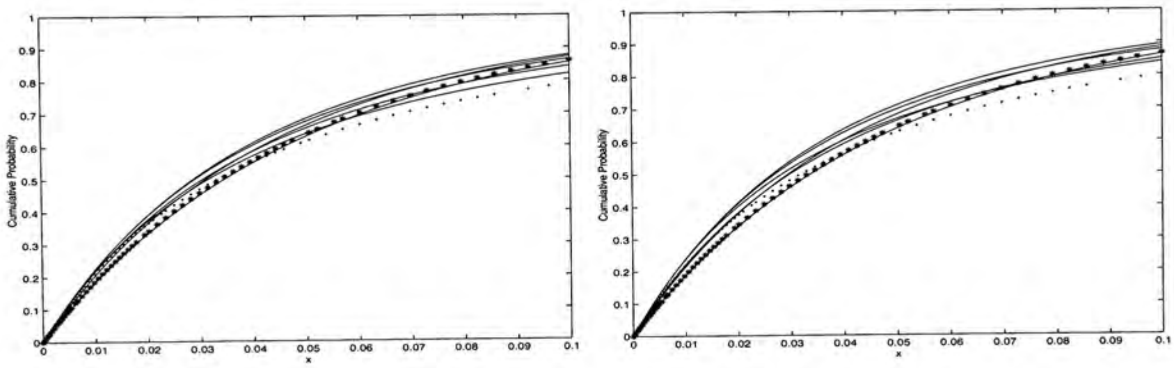



(a) positive (b) negative

Notes:

1. See notes in figure 11.

Figure 15: Plot of conditional distribution functions of excesses for positive and negative returns in 1993

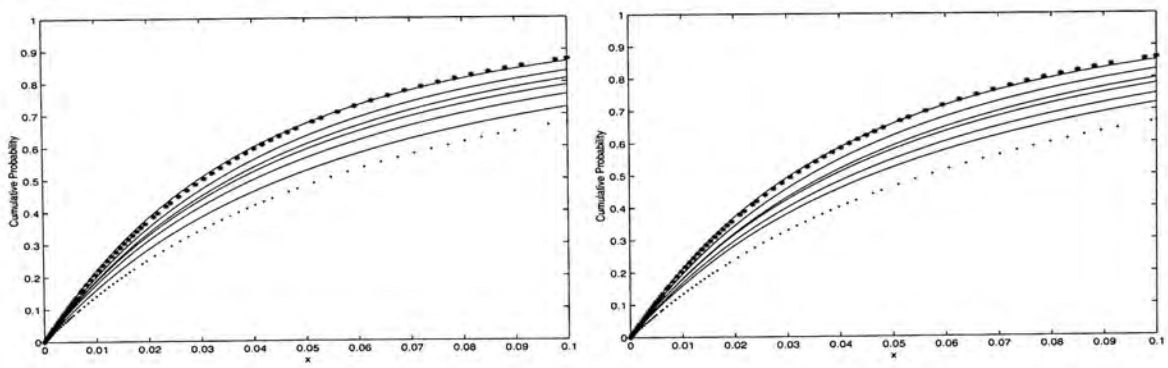



(a) positive (b) negative

Notes:

1. See notes in figure 11.

Figure 16: Plot of conditional distribution functions of excesses for positive and negative returns in 1994

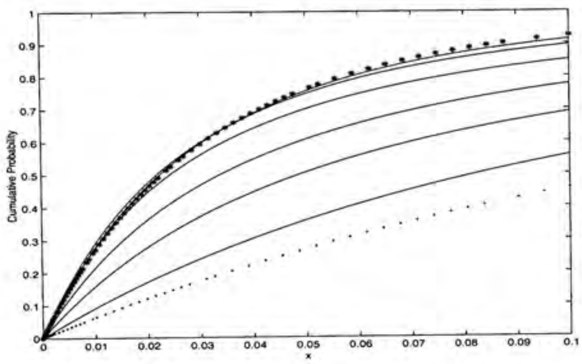



(a) positive (b) negative

Notes:

1. See notes in figure 11.

Figure 17: Plot of conditional distribution functions of excesses for positive and negative returns in 1995



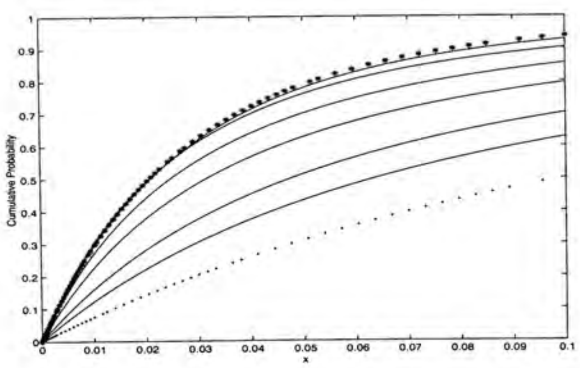

(a) positive

(b) negative

Notes:

1. See notes in figure 11.

Figure 18: Plot of conditional distribution functions of excesses for positive and negative returns in 1996



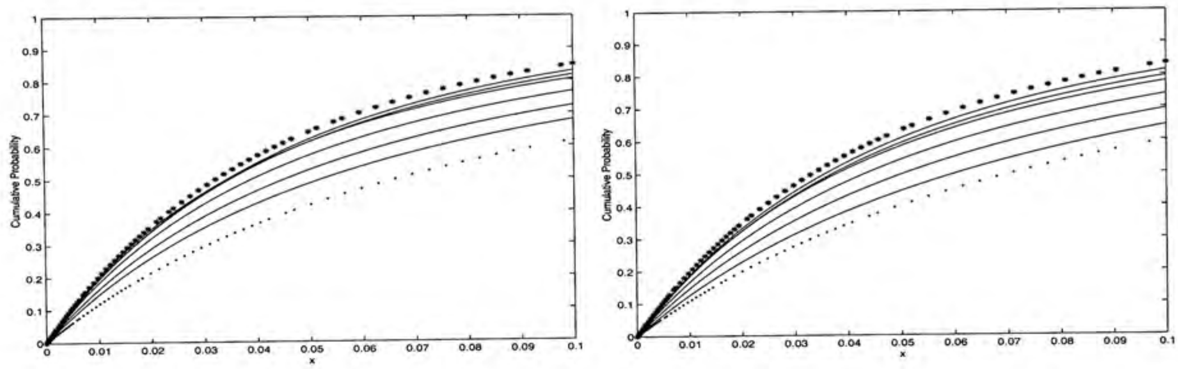

(a) positive

(b) negative

Notes:

1. See notes in figure 11.

Figure 19: Plot of conditional distribution functions of excesses for positive and negative returns in 1997

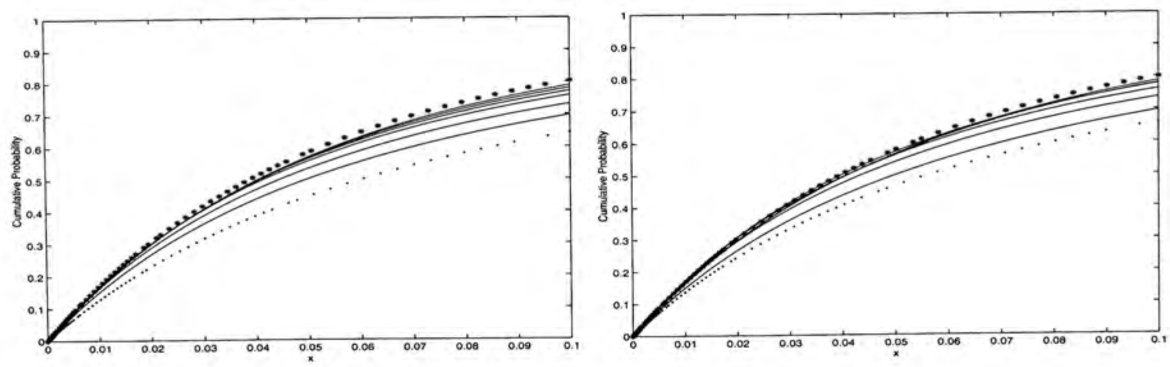



(a) positive (b) negative

Notes:

1. See notes in table 11.

Figure 20: Plot of conditional distribution functions of excesses for positive and negative returns in 1998

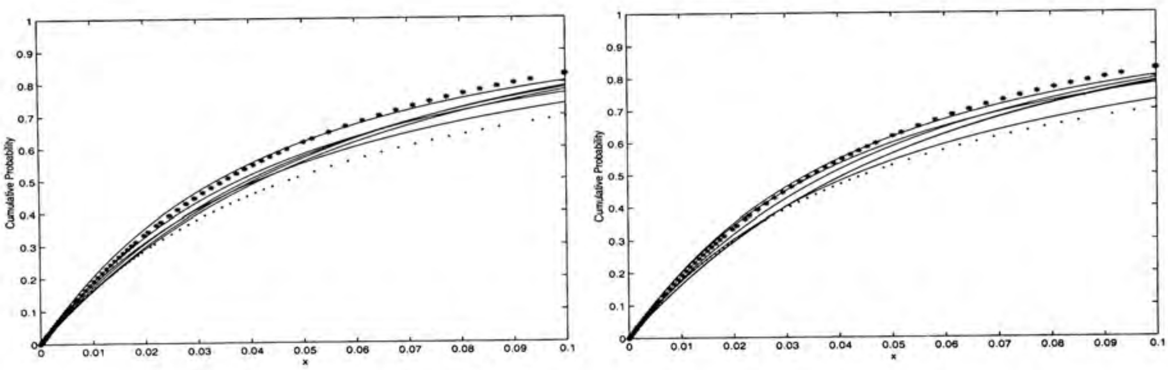



(a) positive (b) negative

Notes:

1. See notes in figure 11.

Figure 21: Plot of conditional distribution functions of excesses for positive and negative returns in 1999



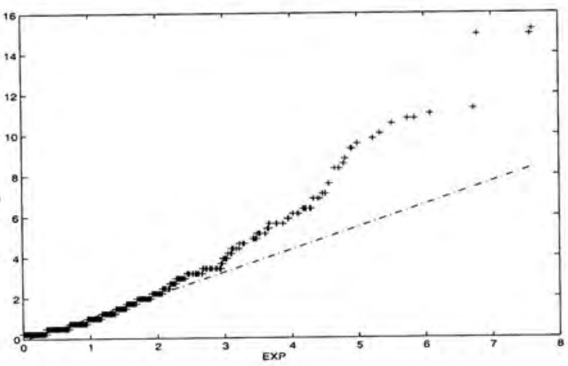

(a) positive

(b) negative

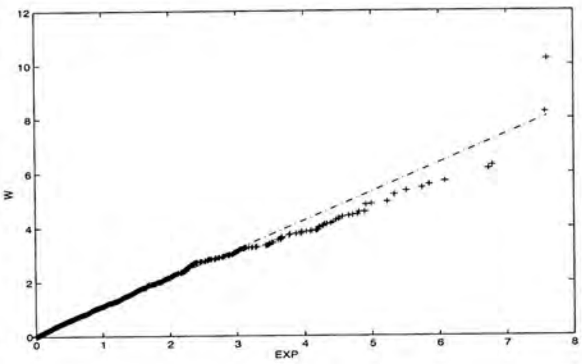
Notes:

1. See notes in figure 11.

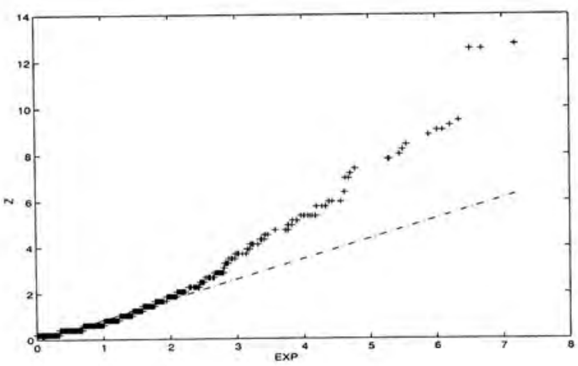
Figure 22: QQ-plots for time durations $z_{t_i}$ and excesses $w_{t_i}$ over the threshold 1% using a homogeneous model



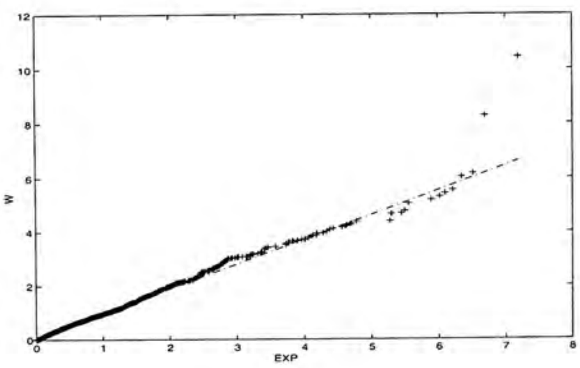

(a) positive $z_{t_i}$




(b) positive $w_{t_i}$




(c) negative $z_{t_i}$

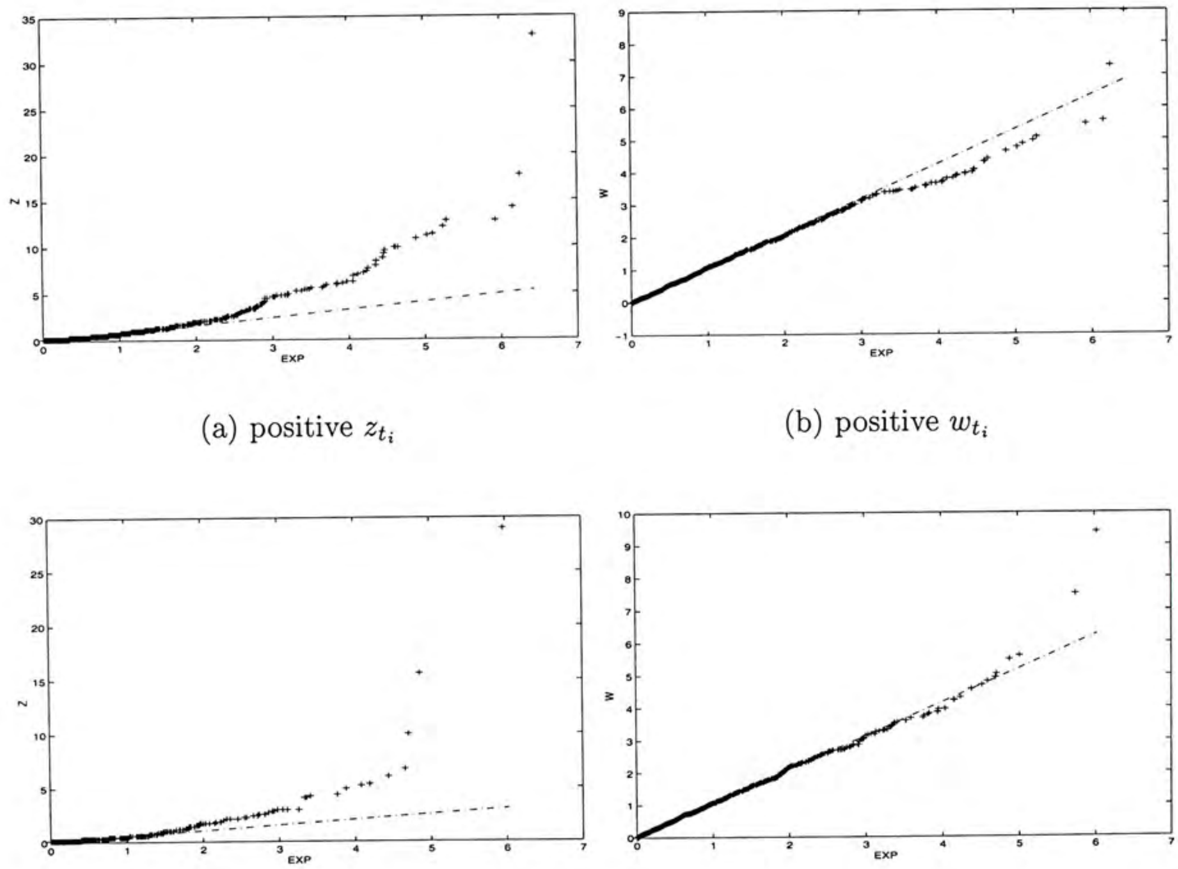



(d) negative $w_{t_i}$

Notes:

1. Panels (a) and (b) show the QQ-plots of time duration $z_{t_i}$ for both positive and negative returns, while panels (c) and (d) present those of excesses $w_{t_i}$ for positive and negative returns. x-axis represents the empirical quantiles of the time durations or excesses. y-axis represents the quantiles of a standard exponential distribution.

Figure 23: QQ-plots for time durations $z_{t_i}$ and excesses $w_{t_i}$ over the threshold 1.5% using a homogeneous model



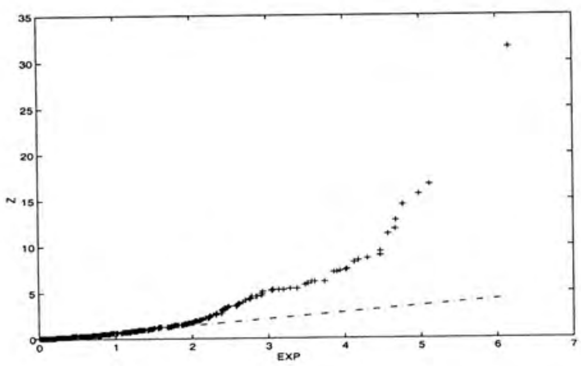

(a) positive $z_{t_i}$ (b) positive $w_{t_i}$

(c) negative $z_{t_i}$ (d) negative $w_{t_i}$

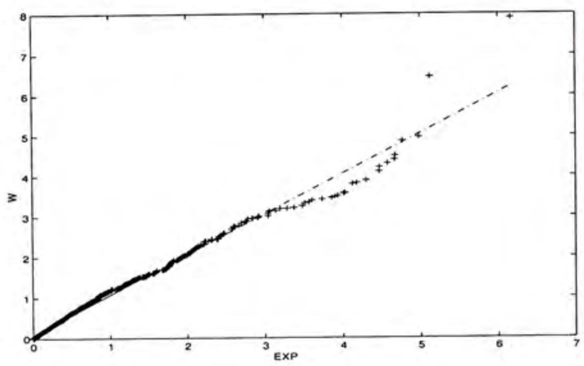
Notes:

1. See notes in figure 22.

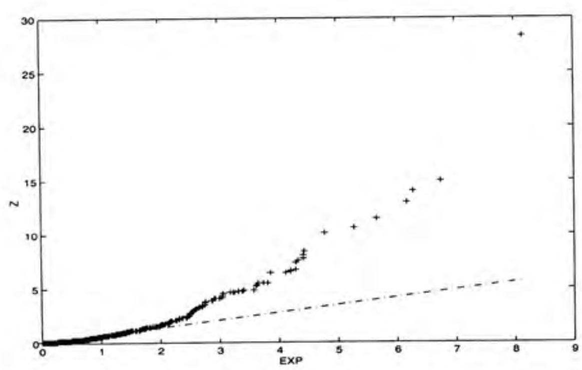
Figure 24: QQ-plots for time durations $z_{t_i}$ and excesses $w_{t_i}$ over the threshold 2% using a homogeneous model



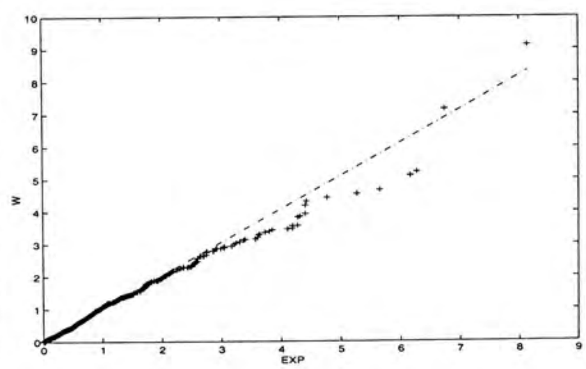

(a) positive $z_{t_i}$




(b) positive $w_{t_i}$




(c) negative $z_{t_i}$

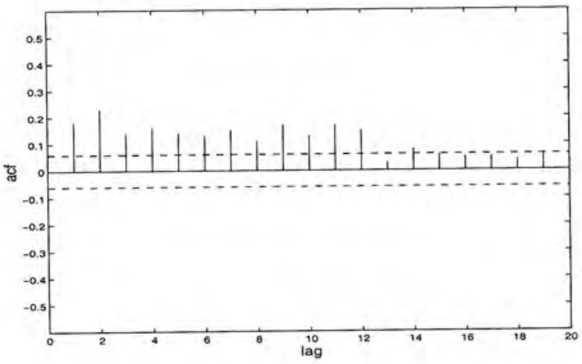



(d) negative $w_{t_i}$

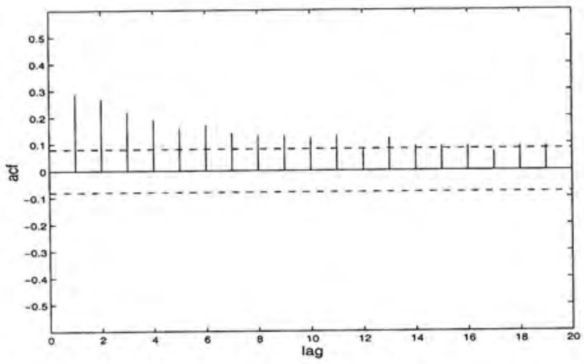
Notes:

1. See notes in figure 22.

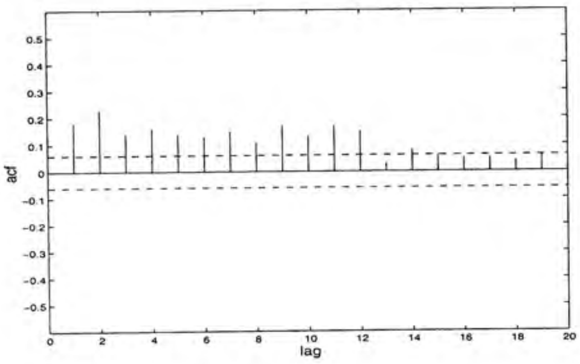
Figure 25: Autocorrelations for time durations $z_{t_i}$ and excesses $w_{t_i}$ over the threshold 1% using a homogeneous model



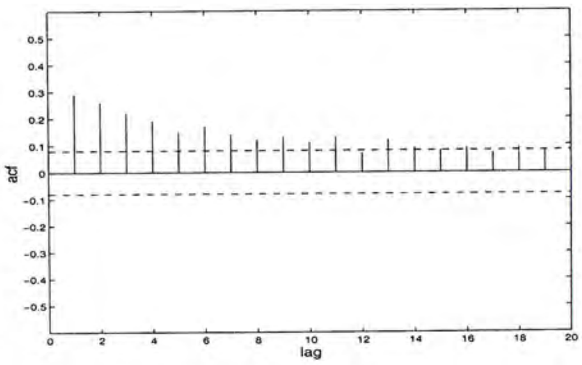

(a) positive $z_{t_i}$




(b) positive $w_{t_i}$




(c) negative $z_{t_i}$

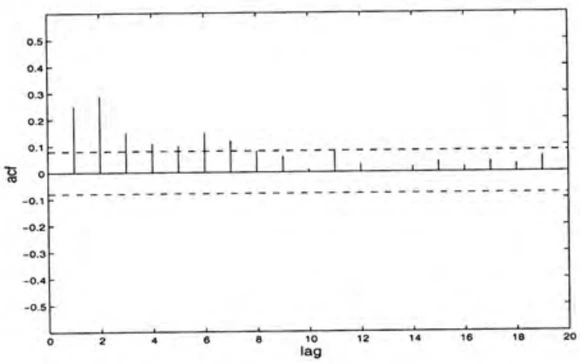



(d) negative $w_{t_i}$

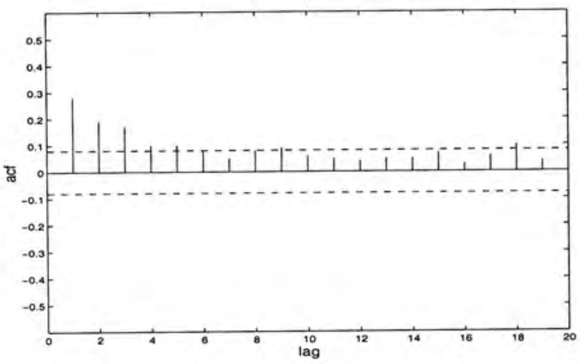
Notes:

1. Panels (a) and (b) show the autocorrelations of time duration $z_{t_i}$ for both positive and negative returns, while panels (c) and (d) present those of excesses $w_{t_i}$ for positive and negative returns.

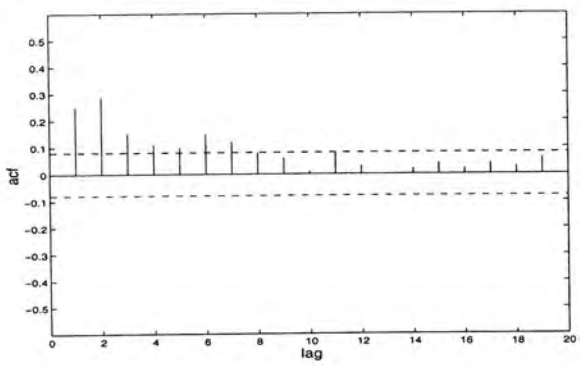
Figure 26: Autocorrelations for time durations $z_{t_i}$ and excesses $w_{t_i}$ over the threshold 1.5% using a homogeneous model.



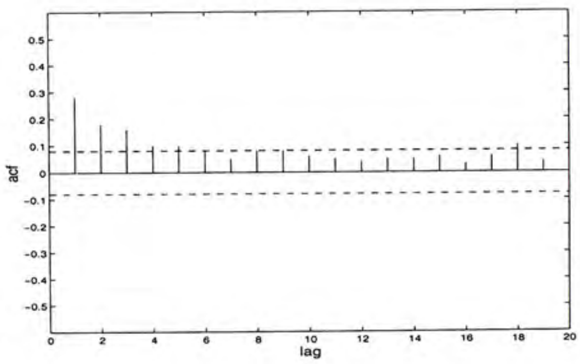

(a) positive $z_{t_i}$




(b) positive $w_{t_i}$




(c) negative $z_{t_i}$

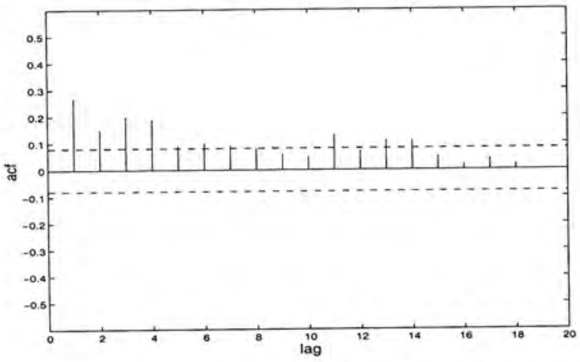



(d) negative $w_{t_i}$

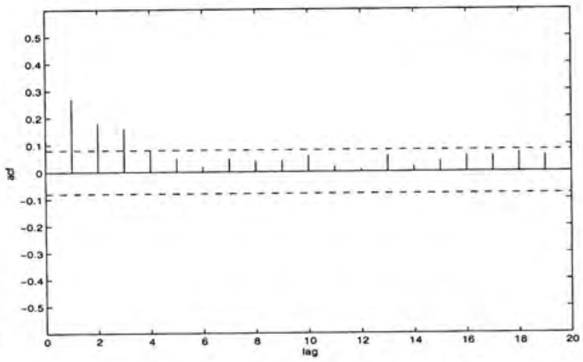
Notes:

1. See notes in figure 25.

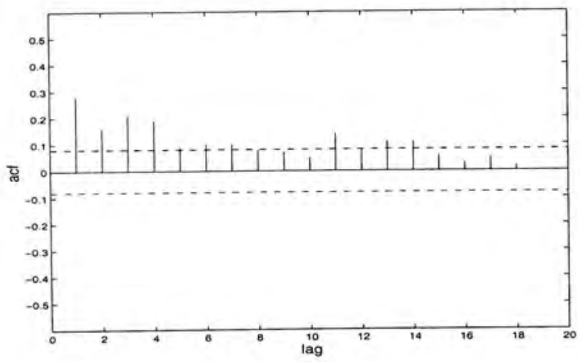
Figure 27: Autocorrelations for time durations $z_{t_i}$ and excesses $w_{t_i}$ over the threshold 2% using a homogeneous model.



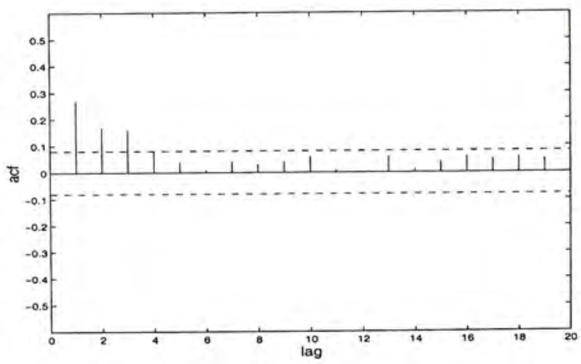

(a) positive $z_{t_i}$




(b) positive $w_{t_i}$




(c) negative $z_{t_i}$

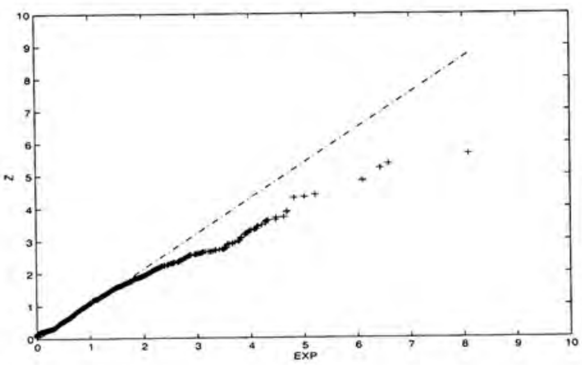



(d) negative $w_{t_i}$

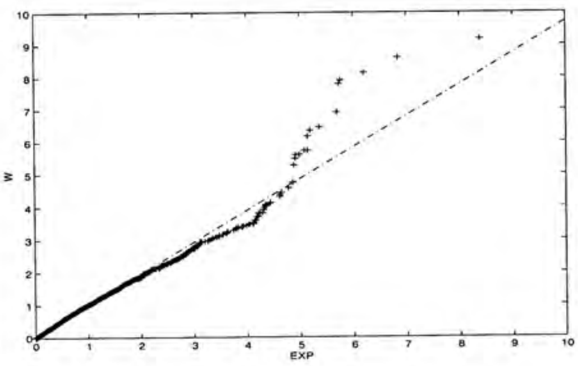
Notes:

1. See notes in figure 25.

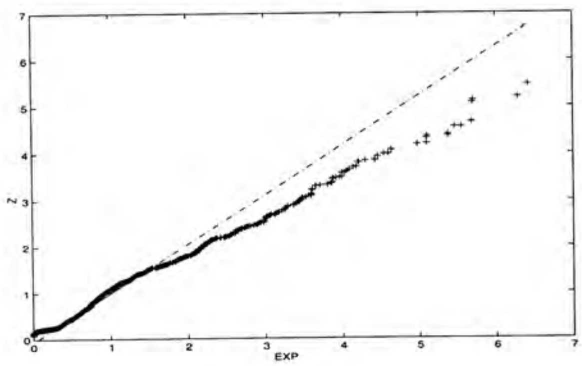
Figure 28: QQ-plots for time durations $z_{t_i}$ and excesses $w_{t_i}$ over the threshold 1% using a inhomogeneous model



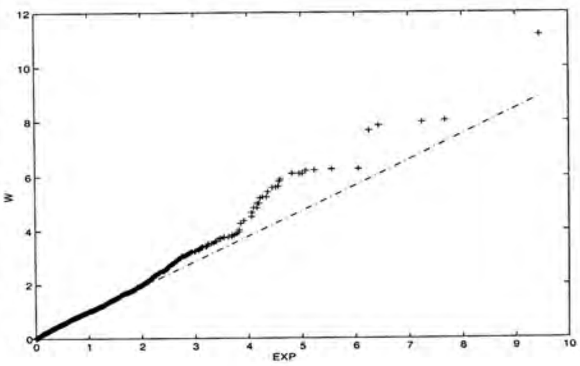

(a) positive $z_{t_i}$




(b) positive $w_{t_i}$




(c) negative $z_{t_i}$

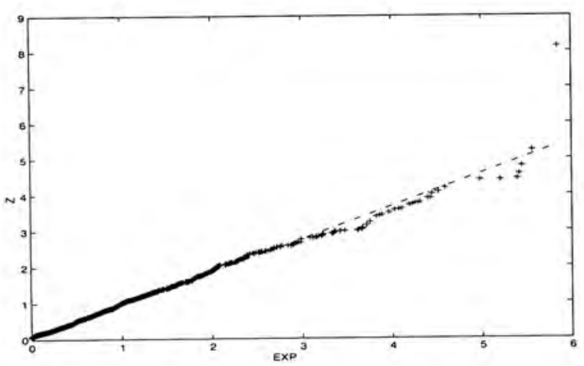



(d) negative $w_{t_i}$

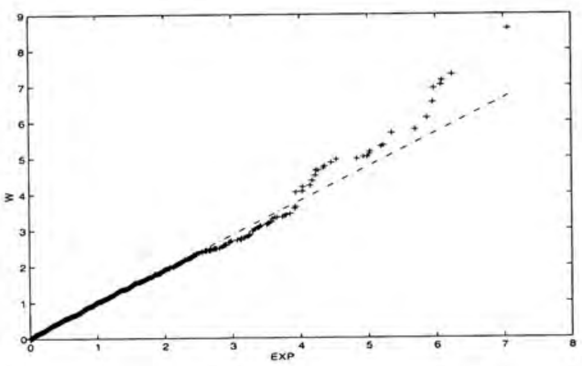
Notes:

1. Panels (a) and (b) show the QQ-plots of time duration $z_{t_i}$ for both positive and negative returns, while panels (c) and (d) present those of excesses $w_{t_i}$ for positive and negative returns. x-axis represents the empirical quantiles of the time durations or excesses. y-axis represents the quantiles of a standard exponential distribution.

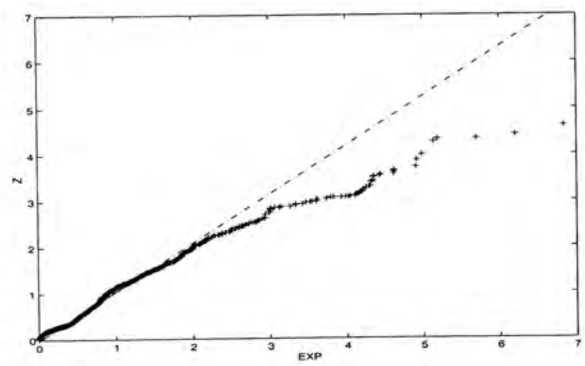
Figure 29: QQ-plots for time durations $z_{t_i}$ and excesses $w_{t_i}$ over the threshold 1.5% using a inhomogeneous model



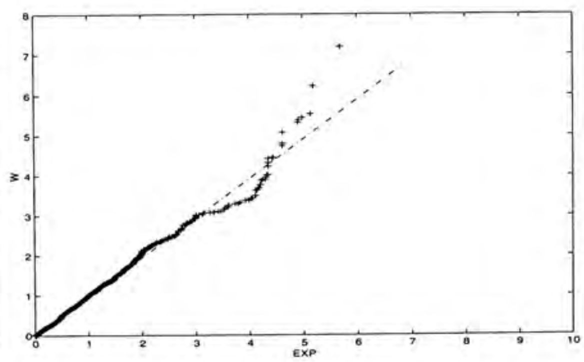

(a) positive $z_{t_i}$




(b) positive $w_{t_i}$




(c) negative $z_{t_i}$

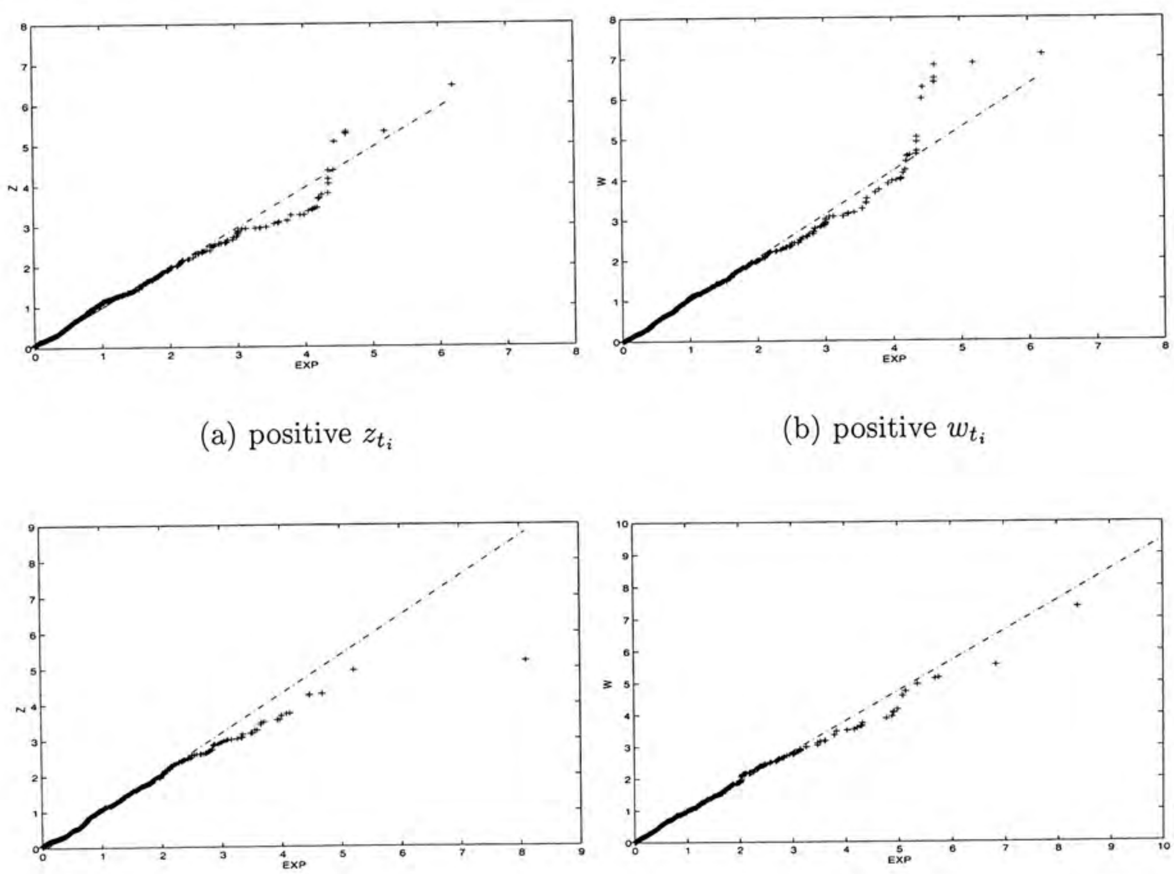



(d) negative $w_{t_i}$

Notes:

1. See notes in figure 28.

Figure 30: QQ-plots for time durations $z_{t_i}$ and excesses $w_{t_i}$ over the threshold 2% using a inhomogeneous model




(a) positive $z_{t_i}$

(b) positive $w_{t_i}$

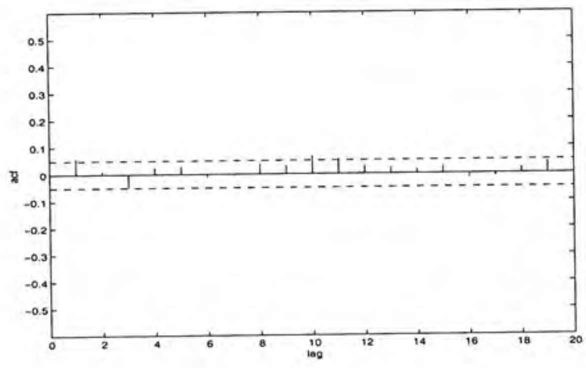
(c) negative $z_{t_i}$

(d) negative $w_{t_i}$

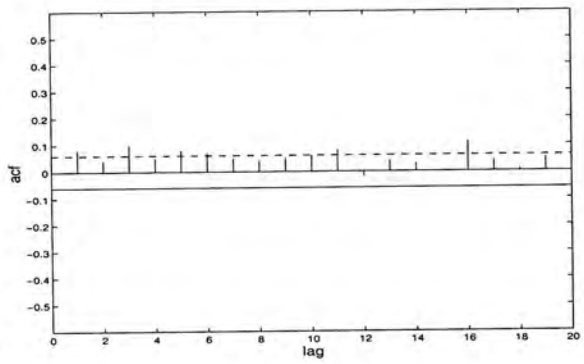
Notes:

1. See notes in figure 28.

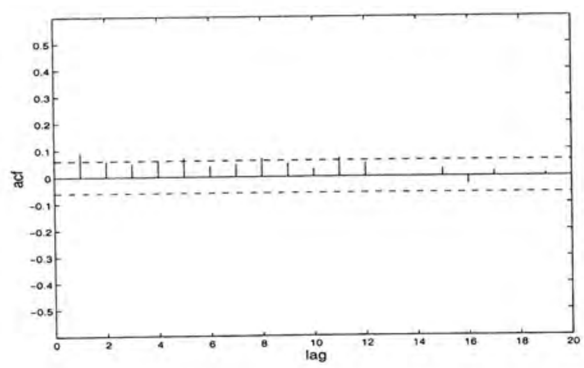
Figure 31: Autocorrelations for time durations $z_{t_i}$ and excesses $w_{t_i}$ over the threshold 1% using a inhomogeneous model



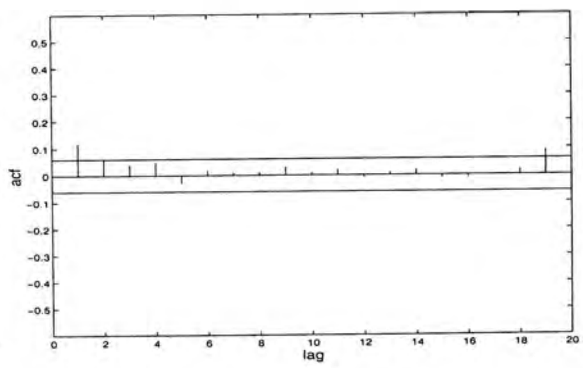

(a) positive $z_{t_i}$




(b) positive $w_{t_i}$




(c) negative $z_{t_i}$

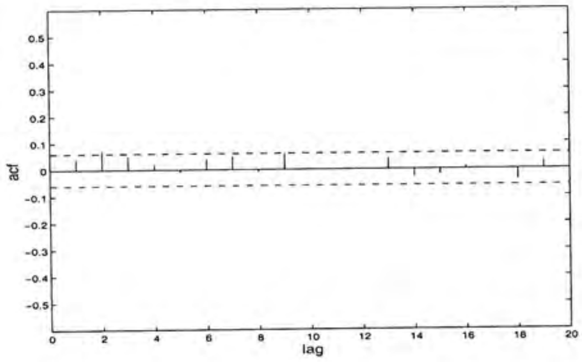



(d) negative $w_{t_i}$

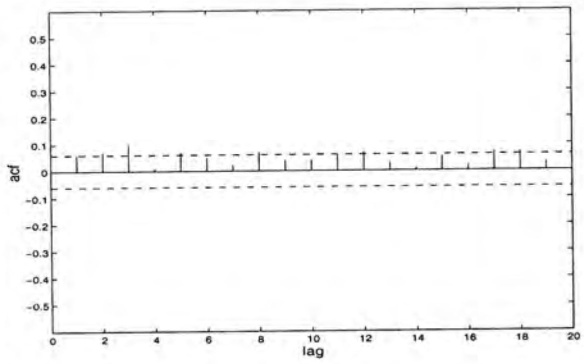
Notes:

1. Panels (a) and (b) show the autocorrelations of time duration $z_{t_i}$ for both positive and negative returns, while panels (c) and (d) present those of excesses $w_{t_i}$ for positive and negative returns.

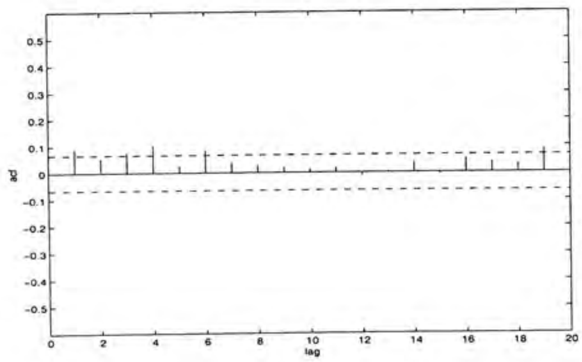
Figure 32: Autocorrelations for time durations $z_{t_i}$ and excesses $w_{t_i}$ over the threshold 1.5% using a inhomogeneous model.



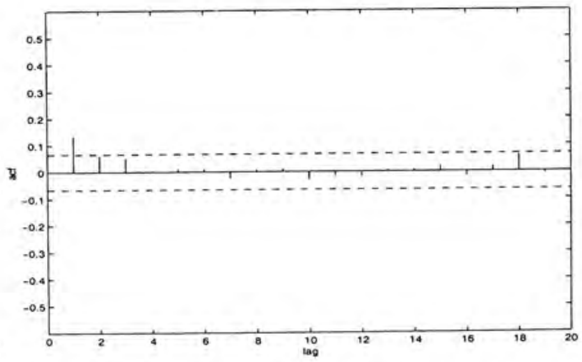

(a) positive $z_{t_i}$




(b) positive $w_{t_i}$




(c) negative $z_{t_i}$

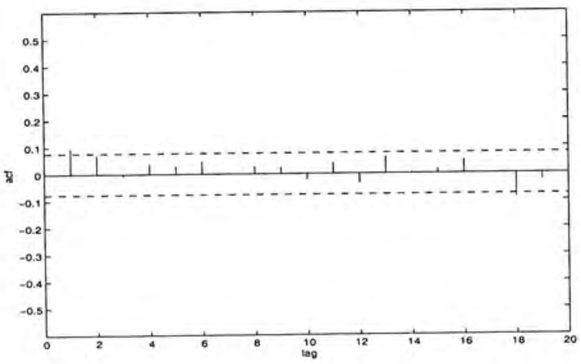



(d) negative $w_{t_i}$

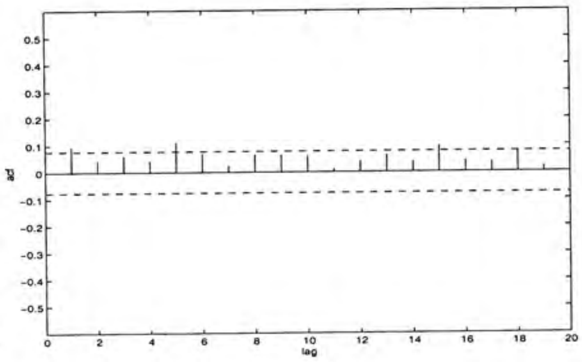
Notes:

1. See notes in figure 31.

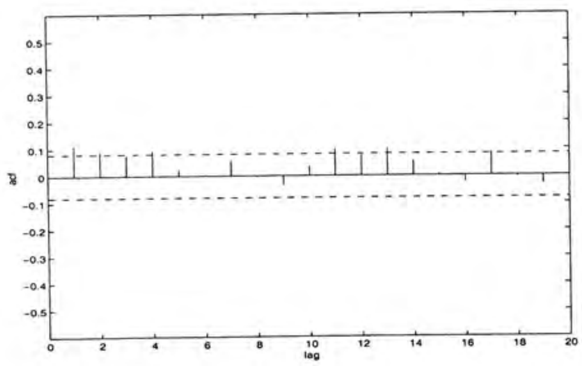
Figure 33: Autocorrelations for time durations $z_{t_i}$ and excesses $w_{t_i}$ over the threshold 2% using a inhomogeneous model



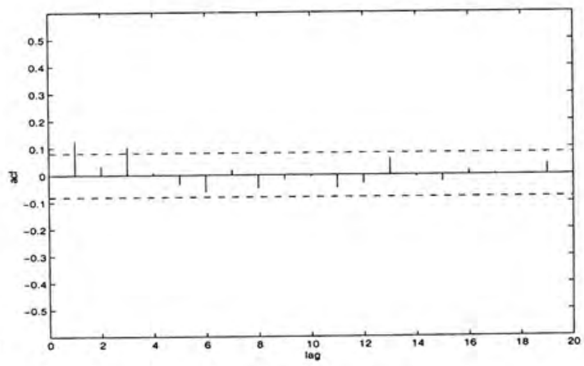
(a) positive $z_{t_i}$



(b) positive $w_{t_i}$



(c) negative $z_{t_i}$



(d) negative $w_{t_i}$

Notes:

1. See notes in figure 31.

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